APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN ENVIRONMENTAL POLLUTION

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Civil Engineering

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN ENVIRONMENTAL POLLUTION"** was prepared by **LIM JING HUI** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Civil Engineering at Universiti Tunku Abdul Rahman.

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ABSTRACT

Real-life environmental issues are complex and highly dependent on various operating conditions, feedwater characteristics and process configurations. As the problems of environmental pollution become more complex, researchers are exploring and studying computationally rigorous intelligent systems for intelligent solutions. Therefore, this study aims to investigate the applications, issues, and challenges of AI-based models in the field of environmental pollution. The objectives of this study are to review the concepts of AI and environmental pollution, conduct the Strength, Weakness, Opportunity, and Threat (SWOT) Analysis of the deployment of AI in environmental pollution, and propose the future trends of AI implementation in the environmental pollution. In this study, a qualitative approach was used in which a total of 191 research articles were extensively reviewed. The SWOT analysis was conducted to assess the potential issues and challenges AI encountered in environmental pollution. The analysis revealed that current AI applications in environmental pollution can produce reliable, accurate and precise outcomes but lack transparency due to unexplainable behaviour. The PESTLE analysis has also been included in this research, which discussed AI application of environmental pollution in political, economic, sociological, technological, legal and environmental factors. At the conclusion of this study, a probable future development of AI in environmental pollution is offered. It is expected that more decision-making systems can be proposed and developed to perform complex environmental decision-making. Last but not least, this research helps to a better understanding of how AI technology was accepted and exploited in environmental pollution. This study can also be used as a reference source for other researchers performing similar research.

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LIST OF SYMBOLS / ABBREVIATIONS

$°C$	degree Celsius
CO	carbon monoxide
CO_2	carbon dioxide
Fe	iron ion
K_a	acid ionization constant
K_b	base ionization constant
L_{Aeq}	equivalent sound level
NO_2	nitrogen dioxide
O_3	ozone
Pb	lead
R	coefficient of correlation
R^2	coefficient of determination
SO_2	sulphur dioxide

ABR	adaptive boosting regression
AGI	artificial general intelligence
AI	artificial intelligence
ANFIS	adaptive neuro-fuzzy interface systems
ANN	artificial neural network
AQI	air quality index
ASI	artificial super intelligence
BOD	biological oxygen demand
BP	backpropagation
C&DW	construction and demolition waste
CNN	convolutional neural network
COD	chemical oxygen demand
DL	deep learning
DO	dissolved oxygen
DoE	design of experiments
DTR	decision tree regression
EPA	environmental protection agency
FBR	fluidized bed reactor

FC	fully-connected
FS	forward selection
GBR	gradient boosting regression
GDR	gradient descent regression
GIS	geographical information system
GM	grey model
GT	gamma test
HSW	hospital solid waste
IoT	internet of things
LGP	linear genetic programming
LR	linear regression
MAE	mean absolute error
ML	machine learning
MLP	multi-layer perceptron
MLR	multiple linear regression
MSE	mean square error
MSW	municipal solid waste
OBD	optimum body diameter
PM	particulate matter
RBF	radial based function
RFR	random forest regression
RNN	recurrent neural network
SS	suspended solids
SVM	support vector machine
SVR	support vector regression
TSP	total suspended particular matter
TSS	total suspended solids
UASB	up-flow anaerobic sludge blanket
WEPP	water erosion prediction project
WHO	world health organization
WPCR	water pollution and control regulation
WT	wavelet transforms
WWTP	wastewater treatment plant

CHAPTER 1

INTRODUCTION

1.1 General Introduction

Artificial Intelligence (AI) is already pervasive in our lives in 2021. From the recommendation systems that understand our preferences for music, movies, and even advertising, humans are already in the Age of Artificial Intelligence. AI implied different things to everyone. According to Lucci and Kopec (2016), Perhaps Raphael stated that AI is the science of making machines to perform a task that needs intelligence if done by a human. According to Psychologists and Cognitive theorists, AI is defined as a human intelligence simulation on a machine that enables the machine to apply appropriate "knowledge" to think and use it to solve a problem (Konar, 2018).

The online survey done by McKinsey & Company received responses from 2395 participants representing their organisation. All respondents represented various regions, industries, company sizes, functional professions, and tenure (Zhang et al., 2021). Of those respondents, 1151 of them said that AI had been adopted in their organization in at least one business function (Zhang et al., 2021). Despite the economic slowdown caused by the Covid-19, half of the respondents claimed it had no impact on their AI investment, while 27% said it had increased (Zhang et al., 2021). From the survey, it can be concluded that AI will be adopted progressively in all industries in the future.

Despite the fact that AI-based models were developed in the disciplines of engineering, computer science, statistics, and mathematics, business administration, economics, and information technology seem to be the main groups applying these methods to assist decision-making processes (Yetilmezsoy, Ozkaya, and Cakmakci, 2011). AI algorithms and their applications are now widely used in medical, pharmacological, biological research areas and just recently, environmental engineering applications (Kim and Park, 2009). However, the main concern of this study is within environmental pollution. AI can be used to involve data screening for pattern detection, potential issues or opportunities identification, or to find similarities between the present and previous circumstances (Cortes, 2000). For example, weather can be forecasted by using this technique, in particular, precipitation forecasting on timescales of about a day. Understanding and knowledge of related factors and their relationships are able to improve through these processes. Besides, AI can also participate in evaluating alternatives to investigate their potential consequences, compare their relative costs and advantages, and provide recommendations for suitable action plans (Cortes, 2000).

The problem of environmental management is becoming a matter of great concern all over the world. Therefore, AI algorithms can be used in the issue of environmental to save time and cost as well as allow the investigation to be more detailed.

1.2 Importance of the Study

There are many ways AI is being used behind the scenes to influence our lives. Whether we are attempting to read our emails, obtain driving directions, or receive music or movie suggestions, AI plays a significant part in our lives.

In this study, a survey of the current application of AI in environmental pollution will be done. It will be beneficial to environmental pollution in terms of future development. For example, possible issues and challenges of AI application in environmental pollution will be determined in this study in order to allow the development of a perfect AI-based model in the future. Besides that, concepts on existing investigations of AI and machine learning (ML) adoption in foreign countries can be studied by reviewing implemented AI and ML technologies in environmental pollution. This paper will show how AI has succeeded in developing adequate tools for decision-support systems, planning, prediction, simulation, design, and modelling for environmental management and protection. This provides a better understanding and more accurate analysis of the strengths, weaknesses, opportunities, and threats of AI application in environmental pollution.

Apart from that, the concepts and information presented in this study can be used as a reference source for other researchers who are performing relevant research. This research will also benefit people who are new to artificial intelligence by teaching them to the underlying theory and functioning principles of AI. Lastly, this study proposed potential trends for the deployment of AI in the future.

In short, AI-based models are being used as the appropriate means to gain more insight and allow more detailed investigations of key variables in real-life environments.

1.3 Problem Statement

Environmental issues in real life are complicated and highly reliant on a variety of operational conditions, influent characteristics, and process configurations. For example, doses of applied chemicals, biomass concentration, temperature variations, hydraulic and sludge retention times, influent flowrate, toxic organic compounds, influent pH, organic loading rates, etc (Yetilmezsoy, Ozkaya, and Cakmakci, 2011). As environmental conditions may be unstable, the proposed system must be continuously monitored and appropriately controlled. Therefore, representative AI-based prediction models can be developed to explain the complicated inter-relationships between the system factors in the process and allow a more detailed investigation of the key variables to be carried out (Yetilmezsoy, Ozkaya, and Caksmakci, 2011).

Nowadays, there are no simple rules to explain the complex and dynamic environmental system. The complexity of the system is currently beyond human understanding (Maher, 2020). Developing indexes or collecting the indicators is the common way for humans to understand the complexity. However, it is only useful as an evaluation indicator; it cannot be used as a decision-making tool. That is because static data or indexes cannot fully explain the uncertainty of the environment. Hence, an AI system that can deeply grasp the challenges and solutions in this complex environment system is needed to overcome these limitations (Maher, 2020).

There are so many environmental problems that cannot be studied through experiments. For instance, the destruction of the biosphere, pollution of air, the diffusion of harmful chemicals in water, global climatic changes and so on (Cortes, 2000). Furthermore, the work is costly and time-consuming (Kim and Park, 2009). Hence, mathematical models and computer simulations are required to gain a better understanding.

1.4 Aim and Objectives

This study aims to propose future trends of AI in environmental pollution. The aim is achieved with the following objectives:

i. To identify the challenges and issues of AI in environmental pollution.
ii. To conduct SWOT Analysis of the development of AI in environmental pollution.
iii. To propose the future development of AI application in environmental pollution.

1.5 Scope and Limitation of the Study

In this study, information, knowledge, and statistics of AI applications in the real-life environmental pollution field will be conducted by reviewing journal articles from previous researchers and online sources such as Google Scholar, ScienceDirect, ResearchGate, etc. Furthermore, an analysis of strengths, weaknesses, opportunities, and threats (SWOT) of AI development in the environmental analysis will be done to identify potential challenges. In addition, the scope of the study will focus on applications of various AI-based models conducted in the field of basic research in environmental pollution, such as waste management research, air pollution-related issues, water and wastewater treatment processes, climate change, and land management.

However, limited access to data and documents is one of the limitations of this study. Some of the resources require specific permission, and some are only restricted to a particular organisation or group of people. These limited sources are able to influence the amount of data gathered and information collected in this study. Lacking of data and information may limit the scope of analysis, as a result, affect the conclusion made. Furthermore, limited time is also one of the limitations of this study that cannot be neglected. The time available for investigating research problems and measuring changes or stability over time is primarily limited by assignment deadlines. And also, this study only manages to propose future development of AI in environmental pollution without developing it due to time constraints.

1.6 Contribution of Study

This research helps to better understand how organisations have accepted and exploited AI technology. Another methodological addition comes from the expertise obtained from using the case study strategy and an interpretative approach, and data gathering procedures. This knowledge might be beneficial in future research on the acceptance and usage of AI in organisations and communities in underdeveloped nations. The data tools used in this study can be used by other researchers to do comparative research in other developing countries. Furthermore, readers will be able to understand the scope of current AI applications in environmental pollution as a result of this research. They will also be informed about potential AI applications that can be investigated in the future.

1.7 Outline of Report

Chapter 1: Introduction

A brief review of the topic of this study has been provided. Problem statement for this research to be carried out is discussed. Apart from that, the aim and objectives of the study are outlined in this chapter too. Lastly, the scope and limitations of the study are also discussed in this chapter.

Chapter 2: Literature Review

This chapter provides a series of literature reviews published by previous researchers and publications. The review topics are all related to AI, environmental pollution and the application of AI in such field.

Chapter 3: Methodology and Work Plan

Research methodology used in this study was discussed in detail in this chapter. The method of data and information collection, SWOT and PESTLE analysis were elaborated on and discussed.

Chapter 4: Analysis and Discussion

In this chapter, the outcome of this study is revealed to evaluate the validity of the research. SWOT and PESTLE Analysis is conducted to show the strengths, weaknesses, opportunities, and threats elements. Besides, proper evaluation is done to determine AI's possible applications in environmental pollution in the future.

Chapter 5: Conclusion and Recommendation

This chapter covers the summary and conclusion of this research. The recommendations are also included in this chapter for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction of Environmental Engineering

2.1.1 Environment

According to Cunningham and Cunningham (2010), humans are living in two different worlds. One is the natural world composed of plants, animals, air, water, and soil. Humans are part of this natural world which is billions of years earlier than everyone. The other world is full of social institutions and artifacts that we used scientific, technological, cultural, and political organizations to build for ourselves. All these elements are a part of our environment. The term "environment" is actually come from French "environner", which means encirclement or surrounding. Thus, the environment can be defined as made of the natural world and the "artifact" or technological, social and cultural world.

2.1.2 Engineering

Engineering can be defined as a scientific- and mathematics-based profession that uses the characteristics of materials and energy sources to create structures, machines, products, systems, and processes (Davis and Masten, 2013).

This means scientists and engineers have fundamentally different perspectives. Engineers must gain experience, practice, and judgement under the supervision of a more experienced engineer as part of their professional growth. Davis and Cornwell (2008) stated that scientists discover things, whereas engineers make them function and workable.

AMERICAN SOCIETY OF CIVIL ENGINEERS
CODE OF ETHICS

Fundamental Principles

Engineers uphold and advance the integrity, honor and dignity of the engineering profession by:

1. using their knowledge and skill for the enhancement of human welfare and the environment;
2. being honest and impartial and serving with fidelity the public, their employers and clients;
3. striving to increase the competence and prestige of the engineering profession; and
4. supporting the professional and technical societies of their disciplines.

Fundamental Canons

1. Engineers shall hold paramount the safety, health and welfare of the public and shall strive to comply with the principles of sustainable development in the performance of their professional duties.
2. Engineers shall perform services only in areas of their competence.
3. Engineers shall issue public statements only in an objective and truthful manner.
4. Engineers shall act in professional matters for each employer or client as faithful agents or trustees, and shall avoid conflicts of interest.
5. Engineers shall build their professional reputation on the merit of their services and shall not compete unfairly with others.
6. Engineers shall act in such a manner as to uphold and enhance the honor, integrity, and dignity of the engineering profession.
7. Engineers shall continue their professional development throughout their careers, and shall provide opportunities for the professional development of those engineers under their supervision.

Figure 2.1: ASCE Code of Ethics (ASCE, 2010).

2.1.3 Environmental Engineering

As modern environmental engineering is such a new science, a better way to begin may be to define it. Some different definitions of environmental engineering may be obtained by searching the Internet and reading journal papers and books written by earlier academics:

- Environmental engineering can be described as the use of engineering concepts to improve and maintain the environment in order to protect human health, protect the beneficial ecosystems of nature, and improve the quality of human life related to the environment (AAEES, n.d.).
- Environmental engineering focuses on safeguarding the environment from the potentially harmful impacts of human activities, protecting the population from adverse environmental factors, and enhancing environmental quality for human health and well-being. (Peavy, Rowe and Tchobanoglous, 1985)

- Environmental engineering reflects good engineering ideas and practices in solving environmental sanitation problems, especially in providing safe, adequate and adequate public water supply; the proper disposal or recycling of wastewater and solid wastes; adequate drainage in urban and rural areas to ensure proper sanitation; and control of water, soil, and air pollution, and the social and environmental impact of these solutions. Moreover, it is concerned with engineering issues in the realm of public health, such as controlling arthropod-borne illnesses, eliminating industrial health risks, and providing appropriate sanitation in urban, rural, and recreational areas, as well as the environmental impact of logical breakthroughs (ASCE, 1977).

Rather than defining what environmental engineering is, we should think about what it isn't. According to Davis and Cornwell (2008), environmental engineering has nothing to do with heating, ventilation or air conditioning (HVAC), and it has nothing to do with landscape architecture. It should also not be confused with architectural and structural engineering functions related to the built environment, such as houses, offices, and other workplaces.

Historically, environmental engineering was only focused on water supply and wastewater treatment, with its roots in the design of sanitation systems and the protection of public health. The previous term, sanitary engineering was replaced by environmental engineering in the 1970s, as the field's focus shifted to cover pollution prevention in air, water, and soil. At about the same time, the design method in this field shifted from focusing on engineering processing systems to focusing more on ecological concepts and processes. Recently, it has been further broadened to address emerging pollutants, chemical exposure of commodities and materials, and efforts such as green manufacturing as well as sustainable urban design (NASEM,2019).

In short, the main goals of environmental engineering are restoration, protection, improvement, and provision. For this purpose, they must follow some fundamental principles, similar to any other engineer, such as planning, designing, constructing, and operating structures, systems, equipments and for the benefit of society as shown in Figure 2.2.

Figure 2.2: Basic principles of problem management. (Šalić and Zelić, 2018).

Basic steps or better, monitoring and perhaps predicting or even preventing harmful activities in the environment is one of the significant duties of environmental engineering. Based on prior understanding, environmental monitoring should guarantee the management of natural resources that contribute to sustainable development via procedures and activities that characterise and monitor environmental quality.

Generally, prevention and predictions are not always effective. If there is a problem occurs, an event loop (Figure 2.2) is started to identify pollutants and track them back to their source. Often, investigating the source is the most challenging task. For example, the source of pollution in a lake may come from anywhere within hundreds of acres of land around the lake or even more. Marine pollution may be much more difficult in determining the source. It is necessary to have a broad understanding of the chemistry and biology of possible contaminants and the industrial or agricultural activities that may cause the pollution (Figure 2.3) to identify problems, evaluate situations, develop plans, and effectively solve problems. Then, according to the contaminated area, a variety of different sciences will participate in finding solutions.

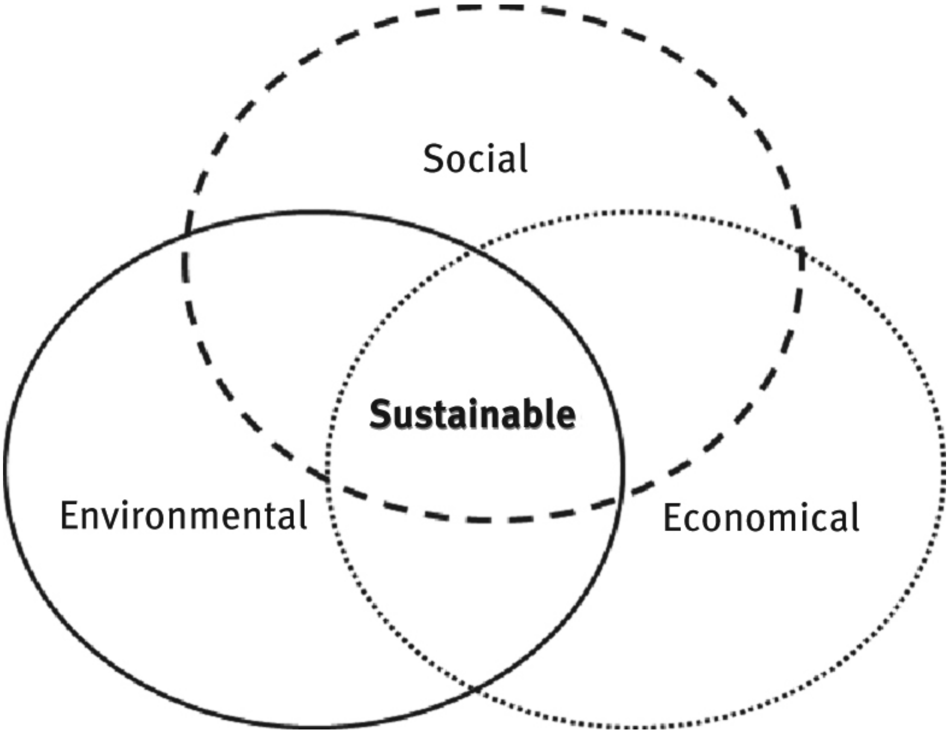


Figure 2.3: Environment engineering fundamentals. (Šalić and Zelić, 2018).

As a result, environmental engineers' duty is to coordinate and collaborate with other engineers in order to discover the best solutions to current problems and make quick progress in cleaning up the environment utilising environmentally friendly technology.

Many environmental problems can usually only be mitigated rather than entirely eliminated, and there are several ethical considerations involved in the process. One of the most contentious decisions that must be taken is whether or not to shut down companies that cause environmental pollution, as this might have significant economic implications. That is why, nowadays, environmental engineers frequently collaborate with businesses to find strategies to minimise or reduce pollution generation while minimising economic costs.

Aside from protection and issue resolution, one of the most significant results of the cycle (Figure 2.2) is acquired knowledge that may be used for future objectives.

2.2 Artificial Intelligence (AI)

Although numerous definitions of AI have developed in recent decades, McCarthy defined it as follows in 2004, “It is the science and engineering of building intelligent devices, particularly smart computer programmes. It's comparable to utilising computers to analyse human intelligence, but AI isn't limited to physiologically observable methods.”

Before this definition, in mathematician Alan Turing’s book "Computing Machinery and Intelligence," he revolutionised history with a single question: "Can computers think?". Turing’s Test was born from there. The Turing’s test is human interrogators will attempt to differentiate the text responses from the computer and human (Turing, 1950). It’s an important part of the history of artificial intelligence and a continuing concept in philosophy because it uses linguistic ideas (IBM Cloud Education, 2022a).

According to Konar (2018), Professor Peter Jackson of the University of Edinburgh decided the history of AI into 3 phases which are Classical period, Romantic period, and Modern period.

- **Classical period (1950s)**

  In this period a group of experts from a variety of areas, including political science, mathematics, engineering, psychology, and economics began to discuss the possibility of developing an artificial brain. The main research work of AI research was carried out during this period.

- **Romantic Period (1960s – mid of 1970s)**

  People were interested in developing machines “understanding” of the natural language during this period. An information processing structure, “semantic net” originated by Quillian was introduced in this period (Quillian,1968). Moreover, a natural-language understanding computer program, SHRDLU by Terry Winograd was also introduced in this period.

- **Modern period (latter half of 1970s – present day)**

  Different systems are being implemented during this period to solve complex real-life problems. In the 1980s, Companies all across the globe adopted an AI software named “expert system”, and knowledge became the focus of mainstream AI research (Newquist, 1994). All in all, in this modern period, the theory and practice of artificial intelligence are constantly being researched.

AI systems usually combine AI, machine learning (ML) and deep learning (DL) to create a complex intelligent machine that can perform given human functions well. Increasingly, all three units are independent parts of the intelligent puzzle of the entire AI system. Both DL and ML are sub-fields of AI, and DL is actually a sub-field of ML as shown in Figure 2.4.

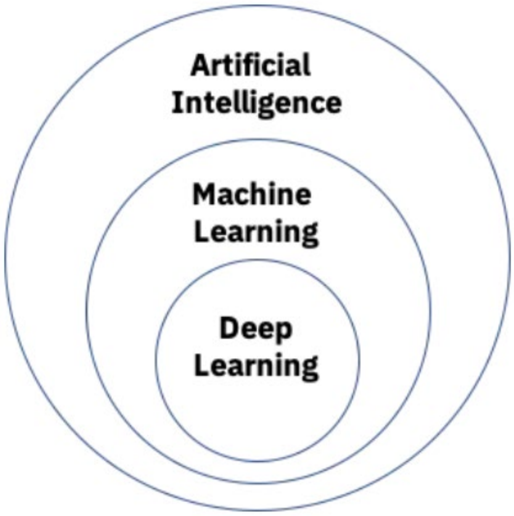


Figure 2.4: Relationship between AI, ML, and DL (Wu,2019).

2.2.1 Weak AI and Strong AI

Over the years, two distinct and ubiquitous artificial intelligence research have been developed. According to one school of thinking, any system or machine that exhibits intelligent behaviour is an example of AI. For this school of thinking, whether the artifact has done its tasks in the same way as a human being is not important. The only criterion is that the program works properly. This approach is called weak AI (Lucci and Kope, 2016).

For this type of AI, "Narrow" may be a more accurate description because it is not weak at all. Therefore, it’s also called Narrow AI. This kind of artificial intelligence usually focuses on performing a single task very well (IBM Cloud Education, 2020a). Although these machines appear to be smart, they operate under more constraints and restrictions than the most basic human intelligence. Narrow AI drives the majority of AI surrounding us today and allows some very extremely strong applications, such as Apple's Siri, Amazon's Alexa, Google Assistant, and self-drive vehicles (IBM Cloud Education, 2020a).

Another school of thinking is focused largely on biological plausibility. In other words, when an artifact displays intelligent behaviours, its performance should be founded on the same principles as a human being. Consider the case of a hearing-capable system. This approach is called strong AI. Strong artificial intelligence is composed of artificial general intelligence (AGI) and artificial super intelligence (ASI).

AGI is a theoretical form of artificial intelligence in which machines have the same intelligence as humans; they will have self-awareness and capable of problem-solving, learning, and planning for the future. ASI, also known as super intelligence, will outperform the human brain’s intelligence and capabilities. Although strong artificial intelligence is still completely theoretical, and there are no actual instances today, this does not mean that AI researchers will not be exploring its development.

2.2.2 Advantages of AI

In many sectors, the application of AI has successfully brought benefits due to its high efficiency and high reliability. First of all, AI can efficiently collect information, undergo further analysis, and determine the new pattern or reveal new knowledge behind the pattern of information through the analysis of data (Liu, Rong & Peng, 2020).

One of the AI application can be seen in the healthcare field. It is undeniable that the performance of a doctor increases during examining the patients when AI is applied. For example, doctors can use computers to evaluate patients' problems and provide precise and accurate information for a patient who is in an emergency (Nadimpalli, 2017).

In addition, when it comes to the commercial sector, AI technology is able to track and monitor the movement of cargo around the world to ensure that packages are delivered to the desired destination on time. Port Botany in Australia is one of the companies adopting this technology (Modgil and Prakken, 2013). Moreover, by integrating such technologies, logistics companies can detect accidents in the supply chain and make necessary modifications to achieve the best results.

Besides, AI also plays a crucial role in environmental pollution nowadays. AI can assist in the monitoring of ecosystems, species, and their interactions. Due to its high processing rates, it is able to provide real-time satellite data to track unlawful logging in forests. AI can manage household water consumption, monitor drinking water quality, forecast when water plant repair is required, and discover subsurface leaks in drinking water supply systems. It may also mimic meteorological events and natural catastrophes to detect gaps in disaster preparation, establish the most effective disaster response approaches, and offer real-time disaster response coordination. (Kyeremanteng, 2020)

The application of AI promotes the process of dissemination of information and knowledge through the existence of the Internet and smart devices, as well as the process of discovering new knowledge from artificial intelligence analysis. The development of IoT and ICT has broken down barriers to information (Goldfarb and Trefler, 2018). In other words, due to the implementation of artificial intelligence, knowledge spillovers have become more accessible than traditional fashion (Liu, et al., 2020).

2.2.3 Risks of AI

Most of the A.I. technology will only work when the user provides them with appropriate input data. However, when the given input data is biased or incorrect in some way, it is likely to have a serious impact on this effect (Mitchell, Michalski, and Carbonell, 2013). A practical example is that a patient lacked the opportunity to get the best treatment from the hospital. This is due to the fact that when a system defines leukaemia as high-priority, it immediately declassifies anaemia as high-priority. As a result, the system cannot provide the most effective treatment for patients suffering from emergency anaemia.

Despite the fact that artificial intelligence offers transformational potential for addressing global environmental issues, it can also accelerate environmental degradation if it is not guided. According to Hao (2019), A life cycle evaluation of the training of many typical large-scale AI models was done by researchers at the University of Massachusetts Amherst. They discovered that the process could generate more than 626,000 pounds of CO_2 equivalent, which is nearly five times the average lifetime emissions of US cars, including fuel as shown in Figure 2.5.

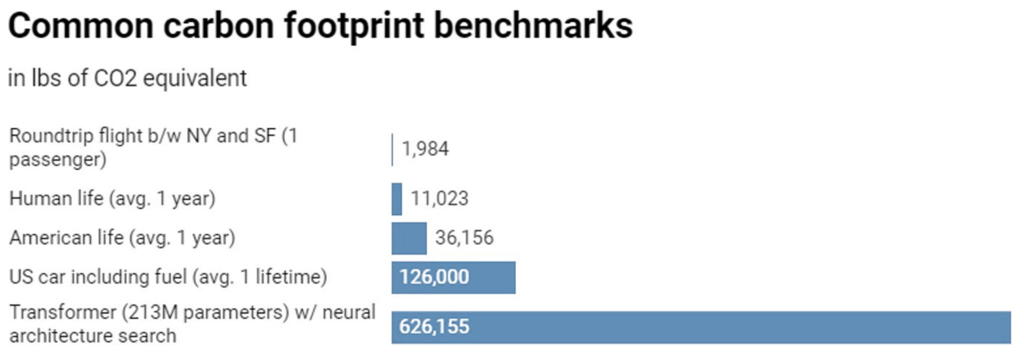


Figure 2.5: Common carbon footprint benchmarks. (Hao, 2019).

In addition, A.I. technology will surely gradually replace labour in specific industries. Thus, the unemployment rate in a country will be increased. Subsequently, the level of economic development will plummet, and people's disposable income will decrease (Modgil and Prakken, 2013).

2.2.4 Limitations of AI

By comparing with humans, the main limitation of the AI system is the lack of general knowledge. Humans have a lot of knowledge, which may not be important for some specific tasks, but may become important (Kingston, 2016). Another limitation is related to the potential liability problem. For example, if artificial intelligence methods are used in the future to build partially or fully self-driving cars, if the self-driving car crashes, which should be responsible in this situation? Despite the fact that this restriction is not technical in nature, it is a major issue that must be addressed. (Chowdhury and Sadek, 2012).

Another drawback of AI-based search methods like genetic algorithms and ant colony optimization is that they can never guarantee the "best" answer. Similarly, it is frequently difficult to properly comprehend the nature of the problem and the answer when utilising AI-based search methods to address difficulties, such as may be the case when using mathematical programming methods. Moreover, there is important empirical evidence that in most cases, AI-based search techniques do generate "good" solutions. In order to understand the problem in-depth, it may be necessary to rerun the model again and again to determine the sensitivity of the solution to various issue assumptions and factors, which is a bit harsh from the perspective of computing resources or runtime (Chowdhury and Sadek, 2012).

2.3 Machine Learning

People are able to enhance their performance in the field of study through learning. For example, after a few years of training, a dental school student improves their ability to restore teeth, while a violinist may be able to play the violin with more artistry. Similarly, ML is the process whereby a machine extracts meaning by exposing it to training data (Lucci and Kopec, 2016).

In other words, ML is the process of training machines through algorithms so that they can execute automatically and intelligently in different situations and sectors or even smarter than humans (Dwivedi et al., 2019). According to Lucci and Kopec (2016), there are three types of ML, which are Supervised Learning, Unsupervised Learning, and Reinforcement Learning.

2.3.1 Supervised Learning

Learning a function with supervised learning is the most straightforward approach (Lucci and Kopec, 2016). Supervised learning is using the labelled data sets to train algorithms to precisely categorise data or predict results. When the model receives input data, it modifies its weights until the model is fitted properly, which is part of the cross-validation process (IBM Cloud Education, 2020b). In other words, the training dataset, which includes inputs and correct outputs are entered into the model that teaches and allows the model to learn over time to obtain the desired output. For example, supervised learning can help organizations solve various practical problems on a large scale, such as sorting spam into a folder different from the inbox. Classification and regression problems are usually solved by using supervised learning (Garbade, 2018), as described in Table 2.1.

Table 2.1: Different between Classification and Regression problem. (IBM Cloud Education, 2020b).

Classification Problem	Regression Problem
Classification uses an algorithm to appropriately distribute test results to separate groups. It identifies particular things in the data set and tries to come up with some conclusions on how to label or define these entities.	To explore the relationship between dependent and independent variables, regression is utilised. It's frequently used to anticipate things like a company's sales revenue.

2.3.2 Unsupervised Leaning

Unlike supervised learning, unlabelled data sets are used in unsupervised learning through machine learning algorithms (Sahla, 2018). This means there is no specific output is provided during the training (Lucci and Kopec, 2016). It's named "unsupervised" learning because it can find hidden patterns in the data without human involvement (Delua, 2021). Unsupervised learning methods are normally employed for the association, dimensionality reduction problem, and clustering, as described in Table 2.2.

Table 2.2: Different between clustering, association, and dimensionality reduction problem (Rani and Kautish, 2018; Delua, 2021).

Clustering	Association	Dimensionality Reduction
It's a data mining approach for sorting unlabelled data into groups based on similarities and differences.	It employs a variety of rules to discover relationships between variables in a given dataset. The output has a feature that somehow correlates or commonly associated with the input.	It is used when there are too many features (or dimensions) in a given data set. It reduces the amount of data input to an acceptable size while still maintaining its integrity.

2.3.3 Reinforcement Learning

Reinforcement learning does not have a fixed data set but a feedback loop between the system and its experience (Goodfellow, Bengio and Courville, 2016). Reinforcement learning is training a machine learning model to make a series of decisions. Agent learning achieves goals in uncertain and potentially complex environments (Osiński and Budek, 2018). Through reinforcement learning, there's no correct answer provided to the agent. In fact, the agent might not be aware of the implications of action in advance. What's more complicated is that even if the effect of an action is known, the value of the effect may be unknown, so it must be learned through trial and error. (Lucci and Kopec, 2016).

2.4 Deep Learning

As mentioned in Chapter 2.2, DL is a sub-field of ML in AI. DL models can make predictions entirely on their own, without relying on humans. DL can be defined as the next generation of ML algorithms that employ several layers to gradually extract higher-level features and knowledge from the original input over time (Wu, 2019). In other work, DL is a type of ML that processes data through a biologically-inspired neural network with a number of hidden layers. These hidden layers enable the machine to go "deep" in its learning, understanding the relationships between variables and therefore achieving the optimal outcome (IBM Cloud Education, 2020c).

2.4.1 Artificial Neural Network (ANN)

As mentioned above, a neural network, also known as an Artificial Neural Network (ANN), is an AI technology that attempts to imitate the problem-solving ability of the human brain (IBM Cloud Education, 2020c). By adjusting the weights assigned to neurons, the ANN model simulates the human brain's ability to learn from repeated inputs (Kim and Park, 2009). ANN are able to self-organize and learn through the historical data patterns and concepts (Baxter, Stanley, and Zhang, 1999). According to Zhang (2016), ANN was a flexible and robust machine learning technique. ANN can be classified into two types. An ANN that has only one hidden layer is a shallow ANN, whereas a deep ANN contains multiple hidden layers (Figure 2.6).

As shown in Figure 2.6, an ANN is made up of a layer of nodes, which comprise an input layer, one or more hidden layers, and an output layer. Each node or artificial neuron is linked to the other node and has its own weights and thresholds. If the output of any single node exceeds a specific threshold, the node is activated, and the data is transmitted to the next layer. Otherwise, data will not be transmitted to the next layer.

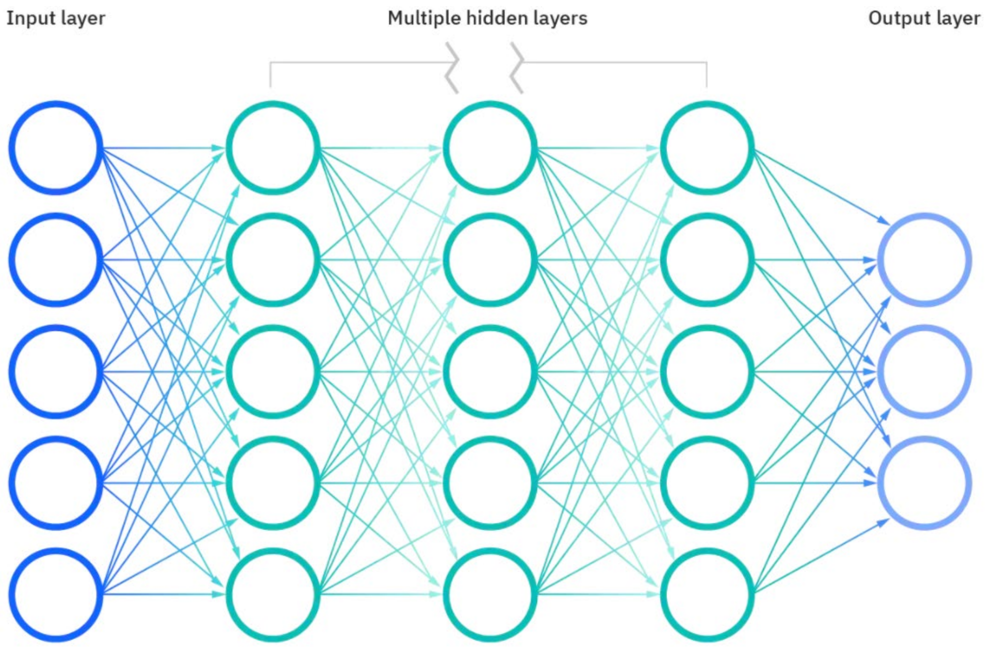


Figure 2.6: Structure of Neural Networks (IBM Cloud Education, 2020c).

Usually, ANNs are feed-forward, which means the data are fed and sent in one direction, from input to output. At present, a variety of ANN algorithms have been proposed. One of the popular ANN algorithms is the backpropagation algorithm (Kim and Park, 2009). It's similar to the feed-forward ANN but moves in an opposite direction, which is from output to input. The Backpropagation network is able to quantify and assign each neuron's mistake and thus allowing the algorithm to fine-tune and fit correctly (IBM Cloud Education, 2020d).

Feedforward neural networks or also known as multi-layer perceptrons (MLPs), are not the only type of ANN. ANN can also be divided into different types with different strengths.

2.4.2 Convolutional Neural Network (CNN)

CNN is similar to feedforward networks, but it's commonly used for classification and computer vision, such as image recognition and pattern recognition (IBM Cloud Education, 2020e). Before CNN, objects or patterns in images are identified by using manual and time-consuming feature extraction techniques. Now, CNN uses concepts from linear algebra, especially matrix multiplication, to discover patterns inside an image, making them more scalable for image classification and object recognition applications.

According to Zhang and Wallace (2015), by comparing to other neural networks, CNN has excellent capacity and superior performance in natural language processing, such as image, speech, or audio signal inputs. That's because Convolutional, pooling, and fully-connected (FC) layers are the three major types of layers found in CNN. The convolutional layer is the first layer in a CNN, followed by an additional convolutional layer or pooling layer, and finally, the FC layer. (Ke, et al., 2018).

The complexity of CNN increases with each layer, identifying more parts of the image. Earlier layers concentrate on basic elements like colours and edges. When the visual data passes through the CNN layer, which starts to differentiate the larger elements or features of the project and finally recognizes the target object (IBM Cloud Education, 2020e).

2.4.3 Recurrent Neural Network (RNN)

According to IBM Cloud Education (2020f), RNNs are similar to feedforward and CNNs, which utilize training data to learn. The difference between them is that RNNs have "memory" because RNNs acquire data from past inputs in order to impact the current input and result, as shown in Figure 2.7. For example, when predicting the next word of a sentence, RNN will use a hidden layer to solve this problem. It has a memory that can remember all previous information (LeCun, Bengio and Hinton, 2015).

Although the input and output of a standard deep neural network are assumed to be independent, the output of RNN is dependent on the previous items in the sequence. These learning algorithms are mostly used to forecast future outcomes using time series data, such as stock market or sales projections IBM Cloud Education (2020c).

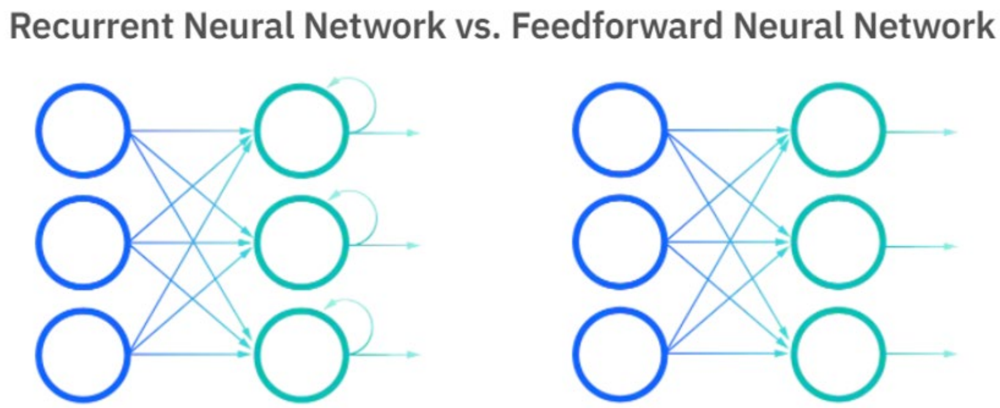


Figure 2.7: Comparison of RNN and feedforward neural network (IBM Cloud Education, 2020f).

2.4.4 Fuzzy Logic

In traditional logic, predicates are only classified as yes-or-no or true-or-false, and nothing is in between. It's similar to Boolean logic, the value 0 refers to False and 1 means True. However, in our world, there are many shades of grey between truth and falsehood. In other words, Real-life problems or situations are very often uncertain or vague. While fuzzy logic algorithm can solve this problem. According to Ozcan (2009), The introduction of fuzzy set theory is to define the uncertainty caused by inaccuracy and ambiguity in real-world applications.

Fuzzy logic is a strong problem-solving approach that is a superset of Boolean or Crisp logic technically (Anaokar and Khambete, 2016). The foundational principle of fuzzy set theory is that each element in a fuzzy set has a degree of membership. As a result, a statement does not have to be either true or false but might be partially true to some degree. This degree is typically assumed to be a real integer in the range of 0 to 1 (Emami, 1997). For example, a logical expression can range from false (0.0 degree of truth) to certainties (1.0 degree of truth) as shown in Figure 2.8.

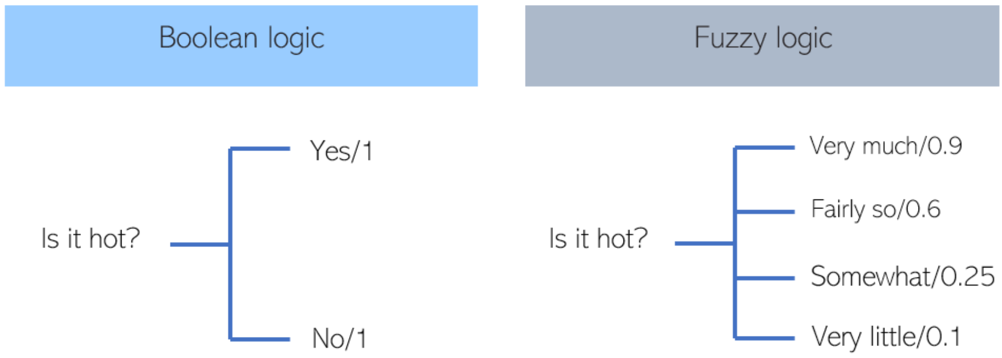


Figure 2.8: Comparison between Boolean logic and Fuzzy logic.

According to Rihani, Bensmaili, and Legrand (2009), fuzzy logic is a helpful technique for modelling very complex systems with unknown behaviours. When it comes to analysing the complex qualitative interactions between variables in environmental systems, fuzzy logic methods provide the benefits of using comparatively basic mathematical calculations in terms of language instead of complex equations utilised in traditional methodologies. Yetilmezsoy, Fingas and Fieldhouse (2011) stated fuzzy logic-based model provides a systematic and transparent analysis for explaining the dynamic behaviour of environment-based problems through a set of logical connectives because it doesn't have to cope with complicated mathematical expressions or laborious empirical formulae.

Based on Jantzen (1998), the four major components of a complete fuzzy system are fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification. In the fuzzification step, the appropriate degrees of one or more membership functions are computed by converting which transforms numeric input and output variables into language words or specialised adjectives like high, low, big, small, and so on.

Fuzzy rule base comprises a few of the rules that cover all potential fuzzy input-output relations. Since fuzzy set theory lacks mathematical equations and model parameters, therefore all uncertainties, model difficulties and nonlinear relationships are expressed as IF-THEN statements in the descriptive fuzzy inference approach (Akkurt Tayfur and Can, 2004). Most people make a decision depending on the situation. A sequence of if-then statements is also used in fuzzy rules (Anaokar and Khambete, 2016). For example, if situation X occurs, then A solution will proceed; if situation Y occurs, B solution will proceed.

The fuzzy inference engine learns how to turn input into related output by considering all of the preset fuzzy rules in the fuzzy rule base (Akkurt Tayfur and Can, 2004). In order to collect all the relationships between the fuzzy inputs and outputs in the fuzzy rule base, two types of inference operators, minimization (min) and product (prod) are used in this step. (Kusan, Aytekin and Ozdemir, 2010). The rules must be merged to determine the decision because the choice is predicated on all the rules of fuzzy inference system.

After that, by using a specified rule base, the linguistic results acquired by fuzzy inference are transformed into a crisp numerical output (actual value) in the defuzzification step (Kusan, Aytekin and Ozdemir, 2010). If the output truth values were exactly obtained from the fuzzification of a given number, this step will be simple.

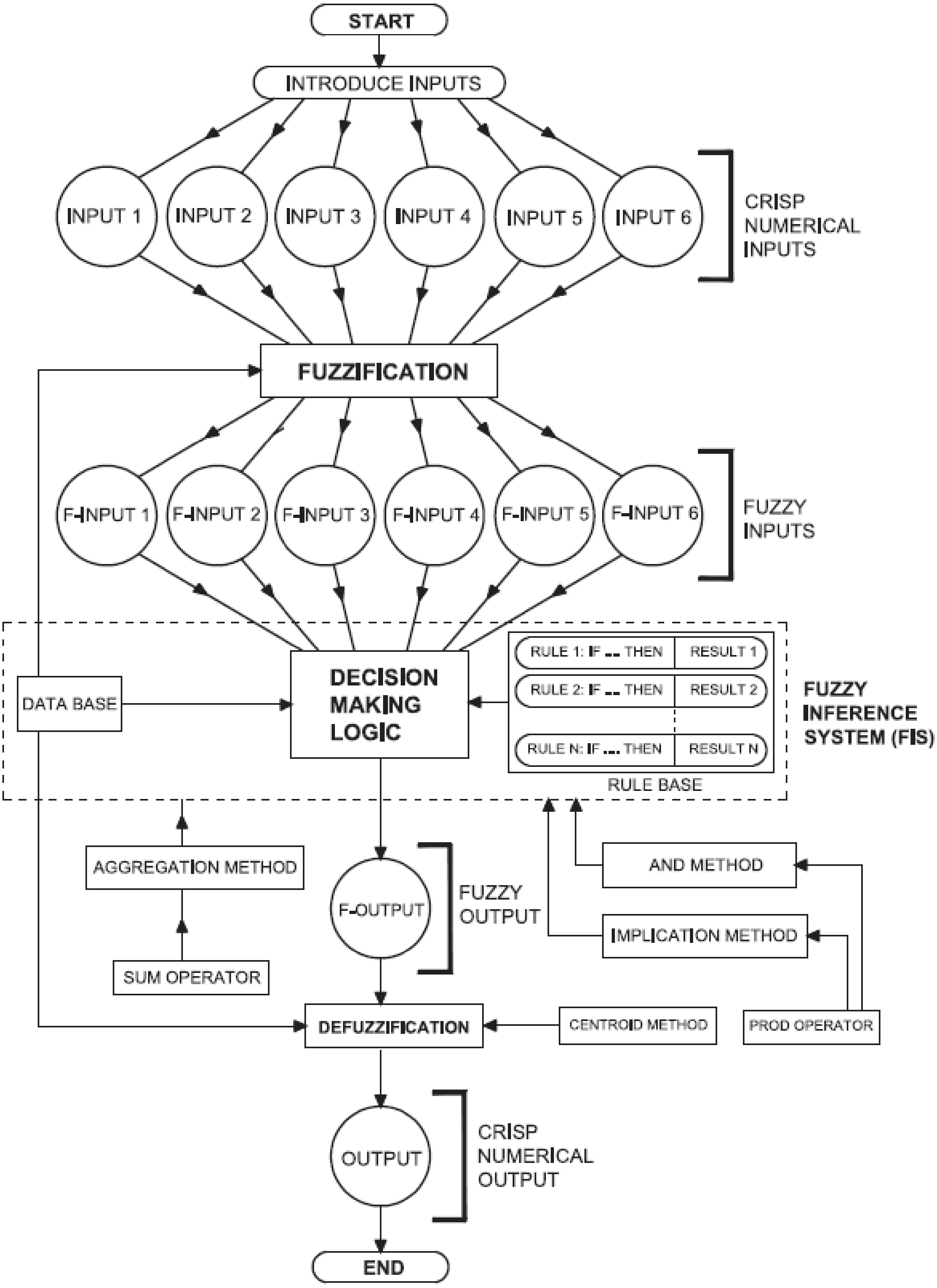


Figure 2.9: Detailed of fuzzy system (Yetilmezsoy, Ozkaya and Cakmakci, 2011).

2.4.5 Adaptive Neuro-Fuzzy Interface Systems (ANFIS)

According to Yetilmezsoy, Ozkaya and Cakmakci (2011), ANFIS is a composition of ANN and Fuzzy logic approaches which are proposed by Jyh-Shing Roger Jang. As the name implies, an adaptive network is a network structure that is made up of nodes and directional links connecting the nodes. Furthermore, some or all of the nodes are adaptive, which means that each of their outputs depends on the parameters of the node, and the learning rule explains how these parameters should be changed to minimise a specified error measure. In other words, an adaptive network is a multi-layer feedforward network, as explained in the previous section (Chapter 2.4.1).

Although adaptive networks have numerous and immediate applications in a variety of fields, one of their most significant drawbacks is the lack of interpretation. According to Wieland, Wotawa and Wotawa (2002), One of the main limitations of ANN is that they cannot show a causal connection between components in the major system; therefore they cannot enhance the user's explicit understanding. Structurally, the network configuration constraint is that it must be feedforward (Jang, 1993). Neural networks are unlikely to be applied in the cases where the opposite is required. Therefore, fuzzy logic technique is needed in these cases for a better understanding (Jang, 1993). As a result, ANFIS is proposed to overcome the combination of ANN and Fuzzy system problems.

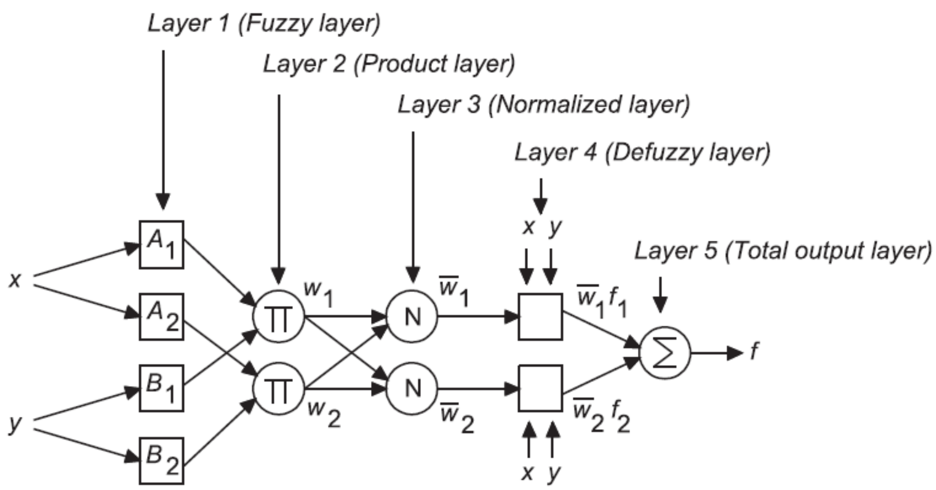


Figure 2.10: Equivalent ANFIS architecture (Yetilmezsoy, Ozkaya and Cakmakci, 2011).

As shown in Figure 2.10, an equivalent ANFIS can be divided into 5 layers (Kumar Tiwari, Bajpai and Dewangan, 2012). The Layer 1 is the Fuzzy layer. Layer 1 is the fuzzy layer. This layer will undergo fuzzification by converting inputs into linguistic phrases or specialised adjectives. The following is the relation of membership between this layer's output and input functions:

$$Q_{1,i} = \mu_{A_i}(x), for\ i = 1,2 \cdots \tag{2.1}$$

$$Q_{1,i} = \mu_{B_i}(x), for\ i = 1,2 \cdots \tag{2.2}$$

where x or y is the input to node i, and A_i or B_i is the linguistic label. As seen in Figure 2.10, inputs x and y are fuzzificated into nodes A1, A2, B1 and B2, respectively.

Layer 2 is the product layer, which is made up of two fixed circular nodes labelled π. All the inputs of this layer will be multiplied and provide the outputs of the product which is defined as follows:

$$Q_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y),\ for\ i = 1,2 \cdots \tag{2.3}$$

where $Q_{2,i}$ denotes the output of Layer 2. The output w_1 and w_2 are the weight functions of the next layer.

The nodes labelled an N in third layer are normalized layer. The i-th node calculates the ratio of the i-th rules firing strength to the sum of all rule's firing strengths.

$$Q_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, for\ i = 1,2 \cdots \tag{2.4}$$

where $Q_{3,i}$ denotes the output of Layer 3. The outputs of this layer are called normalized firing strengths.

The fourth layer is the defuzzy layer whose nodes are adaptive. Every node i in this layer is an adaptive node with a specific function. Every node i in this layer is a square node with a node function:

$$Q_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i x + r_i),\ for\ i = 1,2 \cdots \tag{2.5}$$

where p_i, q_i, and r_i denote the linear parameters set. Parameters in this layer will be referred to as consequent parameters.

Layer 5 is the overall output layer, where the single node in this layer is a circle node labelled Σ that computes the overall output as the summation of all incoming signals. The results can be written as:

$$Q_{5,i} = overall\ output = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i},\ for\ i = 1,2 \cdots \qquad (2.6)$$

Despite the fact that ANN and fuzzy logic models are fundamental of AI, the ANFIS combines the two methodologies and utilises the benefits of both approaches (Yetilmezsoy, Ozkaya and Cakmakci, 2011).

2.5 AI Application in Environmental Pollution

A review of previously published papers using AI approaches for eco-environmental modelling was conducted in this section. Most A.I. technologies are designed to improve the overall performance and quality of the product, which ultimately leads to lower costs and increased profits (Schober, 2020). The latest applications of AI-based prediction models are also investigated in environmental pollution, with key findings discussed in terms of water and wastewater treatment, air pollution control, noise pollution control, solid waste management, climate change as well as soil pollution.

2.5.1 Water and Wastewater Treatment

Monitoring and consistency of measurements as well as laboratory work are challenging and costly tools for evaluating water quality. Also, many of these systems are subject to natural disasters. In some situations, maintenance, control, and calibration become problematic (Ay and Özyıldırım, 2018). Measuring sediment in a river segment is also more challenging than measuring flow. Variables of water quality are typically measured at random time series, and intervals are short. Therefore, the data sets always have a lot of missing values and extensive measurement intervals. As a result, water quality data are the most challenging to analyse, and traditional hydrological methods are also difficult in their analysis (Ay and Özyıldırım, 2018).

According to both the international (World Health Organization (WHO)) and Environmental Protection Agency (EPA))and national Water Pollution and Control Regulation (WPCR) regulations for determining of water quality, there are 50 variables, which include chemical oxygen demand (COD), dissolved oxygen (DO), biological oxygen demand (BOD), total suspended solids (TSS), suspended solids (SS), pH, nitrate, temperature, nitrite calcium, potassium, faecal coliform, and phosphate. Therefore, AI models were invented and gained popularity recently due to their characteristics that can imitate the thinking behaviour of a human.

In Lake Kasumigaura, Japan, Yabunaka, Hosomi and Murakami (1997) studied a BP-ANN model for algal bloom prediction. They concluded that the ANN model worked well for understanding the connections between a collection of specific water quality variables and algal bloom.

Ozkaya et al. (2008) employed the ANN-BP algorithm in another research to forecast the performance of a biological Fe^{2+} oxidising fluidized bed reactor (FBR) and to regulate Fe^{3+} recycling during heap bioleaching. According to the outcomes of the investigation, the suggested ANN method offered a good match between measured and projected concentrations.

Yetilmezsoy and SapciZengin (2009) conducted another ANN-based modelling research to predict COD removal efficiency of up-flow anaerobic sludge blanket (UASB) reactors using diluted real cotton textile effluent. As a result, the ANN model correctly predicted exact and effective COD removal efficiency values with a high correlation coefficient of around 0.83.

Furthermore, Yetilmezsoy and Demirel (2007) used an ANN model to simulate the adsorption of Pb(II) by Antep pistachio (Pistacia Vera L.) shells from aqueous solutions. The proposed ANN model can estimate the effectiveness of adsorption, and the linear regression between the outputs of the network and the related aim is shown to be satisfactory. In the study, the correlation coefficient of the five model variables is about 0.94.

Karul et al. (2000) employed a feedforward ANN model to predict eutrophication in 3 Turkish lakes, which are Mogan Lake, Eymir Lake, and Keban Dam Reservoir. Although the reservoir's complicated and unusual character, they discovered a reasonably high coefficient of correlation (R) between measured and forecasted values. Predictions between measured and

ANN outputs for Mogan and Eymir Lakes were good, with a maximum R of around 0.95. They mentioned that ANN models may properly simulate nonlinear behaviour in the eutrophication process. Furthermore, the models were able to predict a few outliers from data sets that weren't supposed in the ANN's training, such as validation and test data.

Olyaie, Abyaneh, and Mehr (2017) examined the effectiveness of four AI models in predicting DO content in the Delaware River, which is located in Trenton, New Jersey. Radial based function (RBF), multi linear perceptron (MLP), support vector machine (SVM), and linear genetic programming (LGP) were the four AI models used in this research. River discharge, electrical conductivity, pH, and temperature of river water were among the input combinations provided for each AI model. Based on the findings of statistical analysis, it was determined that among the four AI models, SVM could provide the best accurate forecast of DO concentration. Following that were LGP models, which outperformed both ANN-based models. All AI models, on the other hand, were able to retain their forecast accuracy even when the DO content was less.

Hamed, Khalafallah, and Hassanien (2004) constructed two ANN models to estimate wastewater treatment plant (WWTP) performance in Egypt's Greater Cairo area. Over the course of ten months, they acquired daily records from the plant laboratory of BOD and SS concentrations at different phases of the treatment process. As a result, they came to the conclusion that the ANN model was a reliable method which able to forecast WWTP performance effectively.

Onkal-Engin, Demir and Engin (2005) utilised an ANN-BP model to identify the association between sewage sample smells and associated BOD values. Results show that the suggested ANN model was able to correctly categorise sewage samples obtained from various WWTP locations.

According to Zhao et al. (2019), the number of published publications using AI for wastewater treatment research was 19 times more in 2019 than in 1995, and papers had an average of 36 more citations, as shown in Figure 2.11. This means that the performance of AI in this field is becoming more stable and outstanding, and more and more people are willing to employ it.

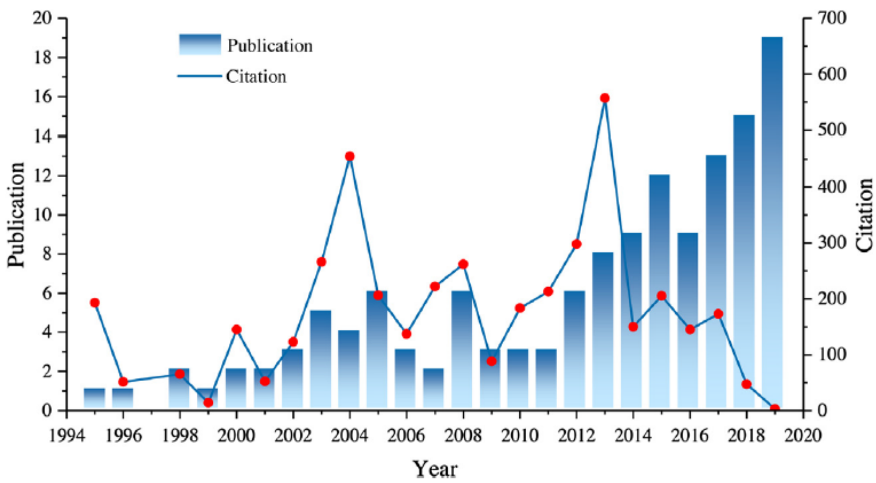


Figure 2.11: Publication trends of AI technology used in wastewater treatment from 1995 to 2019 (Zhao et al., 2019).

2.5.2 Air Pollution Control

Water, noise, and air pollution are all challenges that have arisen as a result of the expansion of the urban economy and technology. Pollution of the air has a direct impact on human health due to pollution and particulate matter exposure, and this has aroused the interest of the scientific community in air pollution and its consequences (Hvidtfeldt et al., 2018).

Due to the volatility and dynamics of pollutants and particulate matter as well as the great unpredictability of time and location, predicting air quality is a challenging task. At the same time, the capacity to monitor, predict and analyse air quality is difficult, especially in metropolitan areas, due to the critical impact of air pollution on residents' health and the environment (Castelli et al., 2020).

Castelli et al. (2020) employ support vector regression (SVR), a variant of SVM, which is a ML approaches for levels of contaminant and particulate matter estimation and air quality index (AQI) prediction for the state of California. Out of all the alternatives studied, radial basis function (RBF) is a type of kernel that make SVR predict accurately. The findings show that using SVR with the RBF kernel can reliably forecast hourly pollutant concentrations such as CO, SO_2, NO_2, O_3, $PM_{2.5}$, and PM_{10}, as well as the hourly AQI for California. As a result, this ML approaches achieved the regulation of EPA with 94.1% accuracy.

In another study, Kartik et al. (2020) used various ML techniques to identify the quality of air in New Delhi, India. As illustrated in Figure 2.12, there are three air pollution monitoring stations in New Dehli, which are Punjabi Bagh, AnandVihar and R.K. Puram. For identifying the AQI of major contaminants such as PM2.5, SO_2, PM10, and NO_2, several regression and classification approaches are used, such as Stochastic Gradient Descent Regression (GDR), Adaptive Boosting Regression (ABR), Linear Regression (LR), Random Forest Regression (RFR), Gradient Boosting Regression (GBR), Decision Tree Regression (DTR), SVR, and ANN. Coefficient of determination (R^2), mean square error (MSE) and mean absolute error (MAE) act as the evaluation value to assess the approaches. In R. K. Puram stations, DTR, SVR, and MLP had the fewest errors. MLP has the fewest calculated errors in Punjabi Bagh, whereas SVR has the fewest calculated errors in AnandVihar. As a result, the best bets for determining the quality of air in New Delhi are ANN and SVR.

Figure 2.12: Air pollution monitoring stations in New Delhi.

Over the last decade, ANN models have been successfully used in a lot of research related to air pollution engineering. For example, Yetilmezsoy (2006) used an ANN model and a new empirical model to determine the optimum body diameter (OBD) of air cyclones by utilizing five operating variables, which are temperature, particle density, gas flow rate, and two design parameters: K_a and

K_b. The study concluded that the maximum diameter deviation of the empirical model and ANN outputs are 1.3 cm and 0.0022 cm, respectively. Despite the fact that both methods produced promising results, but the ANN model was faster, more practical, and better at predicting OBD values.

Recently, several ANFIS have found success in air pollution control. For example, Yildirim and Bayramoglu (2006) used ANFIS to predict the influence of meteorological variables on SO_2 and total suspended particular matter (TSP) pollution levels in Zonguldak, Turkey. According to the findings, the suggested ANFIS model accurately predicted SO_2 and TSP concentration trends by 75-90 per cent and 69-80 per cent, respectively.

Noori et al. (2010) used AI-based modelling to estimate daily CO concentration in Tehran's atmosphere. The study used gamma test (GT) and forward selection (FS) methods to select input variables and build mixed models of ANN and ANFIS. These models were found to be the best in terms of R^2, MAE, and developed discrepancy ratio statistics. In another study, Carnevale et al. (2009) used ANFIS and ANN models to control O_3 and PM_{10} levels in northern Italy. It is found that the source receptor model can effectively evaluate the effect of emission reduction techniques on pollution index and its cost.

Although the principles of atmospheric pollutant dispersion and transport under various meteorological conditions are extremely intricate, several attempts at creating prediction models can aid in the development of a continuous strategy for air pollution control (Akkoyunlu et al., 2010). AI-based models have the potential to play a significant role in designing strategies for effective air quality management and providing a reasonable basis for air pollution control; the premise is under a proper design and evaluation (Yildirim and Bayramoglu, 2006).

2.5.3 Noise Pollution Control

One of the most significant and underestimated environmental issues is urban noise. According to the WHO, noise pollution from traffic and other human activities can influence human life quality and health. Noise, as a disturbing sound, has many impacts on environmental health and should be accurately identified in order to prevent or reduce its effects in city living. Noise monitoring often involves the use of professional and costly devices known as phonometers (Figure 2.13), which are capable of properly measuring sound pressure levels. Due to phonometers needing to be operated by humans, thus periodic fine-granularity city-wide observations are costly.

Figure 2.13: Phonometer Model PPX-130 (Prexiso, n.d.).

Traffic noise is one of the most obtrusive negative effects of the transportation system. The amount of data that can be used to support and indicate the negative impact of noise levels is increasing; therefore, a systematic and effective method is needed to predict and control noise levels. The latest developments in the Internet of Things (IoT) provide an opportunity for low-cost autonomous sound pressure meters. Such equipment and platforms can achieve great spatiotemporal noise measurement in the city. However, by comparing with phonometers, low-cost sound pressure sensors are not accurate and have great variability in measurement.

In a study, Monti et al. (2020) introduced RaveGuard, an autonomous noise monitoring platform that uses AI techniques to increase the accuracy of low-cost sound pressure sensors. RaveGuard was first deployed for almost two months in downtown Bologna, Italy, to collect a large number of accurate noise pollution samples. The resulting data set helps in the design of InspectNoise, a library that can be utilized by IoT platforms. It can achieve similar precision data without using any costly phonometers. Supervised learning algorithms are used in order to close the accuracy gap between the phonometer and an IoT platform armed and fitted with low-cost sensors. According to the result, by comparing with professional equipment, the relative error for the combination of RaveGuard and InspectNoise library is only 2.24%. Thus, low-cost unattended noise monitoring throughout the city is workable.

In another study, Mansourkhaki et al. (2018) employed an ANN model trained by using the Levenberg-Marquardt algorithm was used to forecast the equivalent sound level (L_{Aeq}) derived from traffic. Fifty-one samples were collected in this study from different regions of Tehran, Iran. The input parameters include total hourly traffic volume, average vehicle speed, percentage of various types of vehicles, road slope, the density of buildings around the road segment, and a new parameter called "building reflection coefficient". These data were randomly used in the training, validation, and testing of ANN. The results show that the prediction error of the ANN model is much smaller compared to field measurement data.

Khairjadaan and Okasha (2015) developed a model for the prediction of the noise level by using ANN techniques under the condition of Aman, Jordan. The ANN model that resulted included variables such as traffic volume, composition, speed, and road gradient to describe traffic and site circumstances. The results showed that the ANN model is superior at forecasting traffic noise levels in Amman under local conditions.

Other than ANN, ANFIS also have been employed in this sector. Sharma et al. (2014) implemented ANFIS to assess traffic noise under heterogeneous traffic conditions in Nagpur, India. Traffic noise of 8 locations in Nagpur is predicted and evaluated by using the proposed ANFIS model. The results show that the correlation coefficient between the observed and predicted noise levels is in the range of 0.70 to 0.95. It is observed that the performance of the ANFIS model is greater than the traditional statistical noise model.

Codur, Atalay, and Unal (2017) used both ANN and ANFIS methods for the prediction of traffic noise in the city of Erzurum, Turkey. The input parameter of the prediction process includes a total number of hourly vehicles, heavy vehicles, their average speeds and sound level with 10 percentiles (L_{10}) generated as the output of the model. The results prove that the performance of the ANFIS model is better than the ANN model with regard to R^2 results of ANFIS and ANN are 0.91 and 0.81, respectively.

Apart from traffic noise, the noises produced by the construction are one of the major factor that causes noise pollution. In the study conducted by Zannin et al. (2018), these noise maps were used to mimic the construction of noise barriers, and the effectiveness of the barriers was assessed using ANN and Design of

Experiments (DoE). After that, a functional variable significance analysis was performed on the barrier material's coefficient of absorption and the barrier height. The purpose was to see how these variables affected sound attenuation and the development of acoustic shadows. The findings of ANN and DoE reveal that the absorption coefficient has a significant impact on the noise attenuation supplied by the noise barrier and that the height of the barrier is related to the development of a greater region of the sound shadow.

2.5.4 Soil and Land Pollution Control

Erosion of soil has become a significant challenge for sustainable livelihoods everywhere. Soil erosion is a process that involves the detachment, movement, and consolidation of eroded soil particles on-site or off-site. According to Djeddou, Hameed and Mokhtari (2019), the deterioration of land resources has been one of the consequences of this erosion problem. Soil erosion, which is usually related to watershed features, agricultural practices, and meteorological conditions in the semi-arid region, which cause the degradation of soil fertility, has a series of environmental consequences and a danger to dam storage capacity and agricultural productivity. A proper land management can help to prevent soil erosion. It needs to collect field data and develop predictive models to evaluate different soil protection management options. According to Bujan et al. (2000), on-site measurements of erosion and deposition using traditional techniques are time-consuming and costly.

An accurate forecast of soil erosion rate is critical for the smart and sustainable use of soil resources. Djeddou, Hameed, and Mokhtari (2019) created an ANFIS model to forecast soil erosion in a reasonably broad watershed with a restricted amount of input variables in research. Geographical Information System (GIS) is also employed in this study to evaluate satellite data, which provides necessary data, such as flow direction, distribution of rainfall, slope, land use and cover, and so on, for the study watershed. The erosion prediction models combining both ANFIS and GIS techniques able to predict soil loss and provide the soil erosion spatial distributions. Generating an accurate erosion risk map in a GIS context is critical for prioritising regions of high erosion risk and devising suitable protection methods to effectively manage the Wadi Sahel watershed in the long term.

In another paper, Albaradeyia, Hani, and Shahrour (2010) introduced both the Water Erosion Prediction Project (WEPP) and ANN to predict soil loss and runoff in Palestinian highlands. Analysis shows that the rainfall depth and duration of rainfall events have a big impact on soil erosion. The soil loss and runoff results obtained from the WEPP model are inconsistent with the field data due to WEPP underrated both soil loss and runoff. However, the analysis and observation using ANN are very consistent. Research shows that ANN models can be used as management tools for predicting runoff and soil loss.

In environmental protection, flood management, forestry, and agriculture, high-resolution maps of soil characteristics are regarded as the most significant inputs for policymaking and decision-making. Soil characteristics are usually obtained primarily from field surveys. As mentioned above, field soil study and measurement are time-consuming and costly, as well as their application in a large area is limited. As a result, high-resolution soil property maps are only accessible for a limited number of regions, and they are almost always obtained for research purposes. Zhao et al. (2018) introduced ANN models to generate high-resolution maps of soil properties. It was discovered that with reasonable accuracy and minimal cost, ANN can be used to forecast high-resolution soil organic content, soil drainage classes, and soil texture over a landscape.

In order to promote the diversification of forest land management methods, it is usually necessary to draw large-scale forest attribute maps. Moisen and Frescino (2002) investigated five modelling strategies to find the best tool for map jobs, which are multiple adaptive regression splines, generalized additive models, linear models, classification and regression trees, and ANN. The results show that all technologies have proven effective in an automated environment. The advantages of multivariate adaptive regression splines and ANNs over the other three approaches in terms of predicting ability were clear when their potential mapping capacity was evaluated using simulations. In real data runs, all five approaches show relatively slight changes.

2.6 Summary

In short, the implementation of AI provides numerous benefits to environmental pollution. This chapter reviews the literature on the applications of AI in environmental pollution. However, an in-depth discussion regarding the AI and its components (ML and DL) as well as Fuzzy logic were carried out in this chapter in order to have a clearer picture and a more comprehensive understanding of AI. Undeniable, the application of AI contributes benefits to environmental pollution. Although the applications of AI in environmental pollution are vast, but the implementation of AI is more on prediction. There are many fields yet to be explored, such as decision-making systems, etc. The methods of how this research study was done will be discussed in chapter 3.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

In this chapter, the research methodology used to achieve established goals and objectives will be discussed. This research work can be divided into four main parts, which are reviewing existing research work related to AI, environmental engineering, and AI adoption in the environmental pollution field, SWOT Analysis, PESTLE Analysis, and the future development of AI in the environmental pollution field.

3.2 Research Methodology Flowchart

This research work began with collecting the information related to AI, ML, ANN, Fuzzy Logic, and environmental pollution. The information was obtained from journals, articles, books, and official websites of the organization. For the convenience of research, they are classified into different categories. For example, the categories can be divided into AI, ML, Fuzzy Logic, and environmental pollution components. The classification of research papers can prevent the mixing of different ideas when researching different papers at the same time.

After an in-depth literature review of AI and environmental pollution, potential problems were identified to formulate the problem statements. Having a clear and accurate problem statement is essential because it allows the researcher to determine the purpose of the ongoing research. After that, the aims and objectives were established through the problem statement. There are four aims were formulated in this research. These aims were summarised into four different sentences that the researcher hopes to achieve at the end of the research project.

Data collection will then be collected. In this study, most of the information comes from the research journals of the main sources for literature review. For example, Google Scholar, Research Gate, Science Direct and so on, Next, a SWOT Analysis was performed to determine the challenges and issues of AI in environmental pollution. The SWOT Analysis process was carried out by identifying the strengths, weaknesses, opportunities, and threads of AI adoption through the literature review. PESTLE Analysis was also conducted in the study. PESTLE Analysis specified the politics, economy, society, technology, law, and environment when discussing the AI applications in environmental pollution.

Finally, based on the results of SWOT and PESTLE analysis, the future development and opportunities for the AI application in environmental pollution were proposed. The detailed data analysis will be discussed in chapter 4. Figure 3.1 shows the summary flow chart of the work plan for this study.

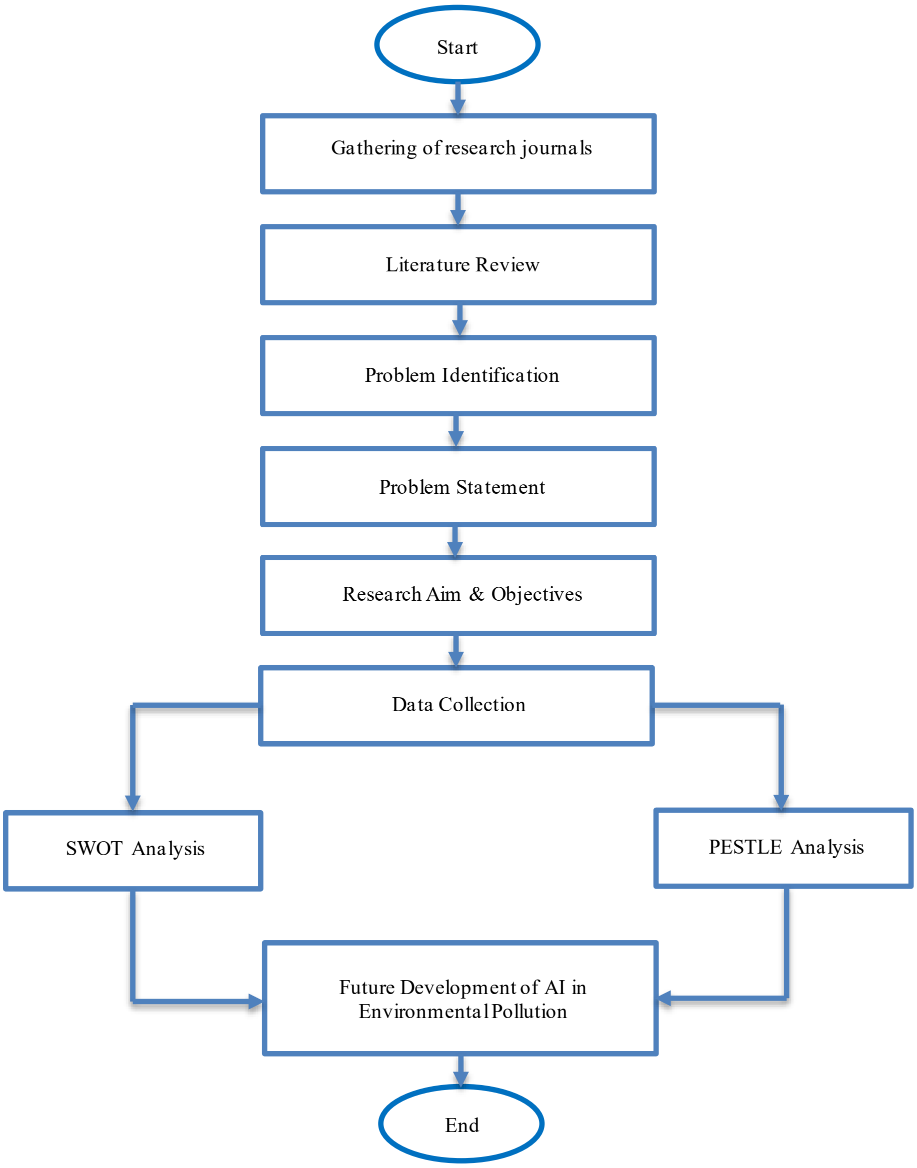


Figure 3.1: Research Methodology Flowchart.

3.3 Research Definition

Research is a set of processes for gathering and analysing data in order to gain a better knowledge of a subject or situation (Creswell, 2008). According to Kothari (2004), a rational and systematic search for the most recent and relevant knowledge about a particular topic of interest is defined as research. In short, it is an investigation that determines solutions by objectively and systematically analysing scientific and social problems. A good research uses a systematic method to collect accurate and reliable data. The SWOT and PESTLE Analysis of AI application in the environmental pollution field can be considered as exploratory research. As the name implied, the researcher will undertake the exploratory studies to investigate a series of questions. According to Saunders, et al. (2019), it’s a kind of research to uncover or verify specific hypothesized issues or problems which little is known.

3.4 Research Methodologies

There are two types of methodological approaches, which are quantitative research and qualitative research. The term "qualitative" refers to an emphasis on entity qualities, processes, and meanings that aren't experimentally proven or quantified in terms of frequency, intensity, amount, or number. Quantitative research, on the other hand, focuses on measuring and analysing causal connections between variables rather than processes. In this study, the qualitative approach has been adopted wherein an extensive review of research articles had been carried out.

3.4.1 Data and information collection

Data and information collection were done in this research by accessing historical research journals, books, and official websites via Internet resources. The literature review is an important stage in the development of research projects. The beginning of the literature review process involves identifying appropriate literature. The journals and articles reviewed in this study are accumulated from well-known journals such as Applied Intelligence, Environmental Progress & Sustainable Energy, International Journal of Environment and Pollution, Natural and Engineering Sciences, Journal of

Environmental Health Science and Engineering, et al. These well-known journals provide a set of initial journals to start the review.

Besides, the primary data was used for research studies. The most reliable source of information is the primary source, as it only publishes the original research. The primary data such as articles, journals and websites had contributed a lot to carry out this study. The primary data were obtained easily through many sources like Google Scholar, Research Gate, Science Direct and Dissertation. Keywords are those words that capture a paper's essence. Keywords such as AI in environmental pollution, ANN or ANFIS in such applications were used for journal article searching. Not only primary sources but secondary sources and reference guides were also used in this research. Secondary sources of literature are those derived from primary sources such as textbooks and newspaper articles.

3.4.2 SWOT Analysis

In order to analyse the AI application in environmental pollution, SWOT analysis was conducted in this research based on the existing technologies and research papers reviewed in the literature review under Chapter 2. SWOT stands for Strengths, Weaknesses, Opportunities and Threats, respectively. In general, the primary goal of SWOT analysis was to investigate the positive and negative effects of internal and external environments on a company or individual life situations. As shown in Figure 3.2, the internal environment can be related to the strengths and weaknesses of the company or organisation. The external environment can be related to the opportunities and threats of the organisation (Madsen, 2016).

Strength is the property that makes something more valuable than others by adding value to it. In other words, if something brings the organization an obvious advantage, then it only can be said as a strength. In this study, the organization is referred to as AI application in environmental pollution. The Strength element represented the components contributed by the development of AI-based models or AI systems in environmental pollution.

Contrary to strength, weakness means something more disadvantageous than other things. Weakness refers to the lack of the form and ability required for something. In this research, weakness refers to the limitations observed through the implementation of AI. In order to identify and determine the unpleasant truths and limitations of AI application in environmental pollution, weaknesses analysis must be conducted honestly. Weakness has a negative impact on the efficiency of an organization and makes it less competitive. The organization was unable to respond to new problems or opportunities. Hence, it's important to determine and improve the weakness elements.

Opportunities are the chances or openings for something positive to occur. Opportunities can also be defined as the chances to produce beneficial results for the organization due to environmental analysis (Gürel and Tat, 2017). Opportunities are the external positive factor that enables the AI application in environmental pollution to leverage its strengths to solve the limitations or neutralize the threats.

A threat is a situation or condition that prevents the realization of an activity. In other words, threats are something that can affect the overall performance of AI applications in environmental pollution from the external environment. According to Gürel and Tat (2017), a threat is a factor that makes goals difficult to be achieved. Thus, it is essential to initiate the action to tackle the threat.

Figure 3.2: SWOT Analysis (Xhienne, 2007).

3.4.3 PESTLE Analysis

After the SWOT Analysis, the PESTLE analysis was applied in this research. As mentioned above, PESTLE is a mnemonic that stands for Political, Economic, Social, Technological, Legal, and Environmental.

Since the 1960s, PESTLE analysis has been the most widely utilised model for analysing macroeconomic factors that may affect the decision-making process by businesses and professionals (Del Marmol et. al., 2015). PESTLE is able to detect, examine, and classify the effect of all these variables. Thus, threats that cannot be directly managed may be identified easily and quickly, thereby assessing possible high risks. Various situations can be conceived, and potential alternatives can be developed to overcome the threats.

Political factors determine the degree of government influence on the economy or specific industries. Economic factors determine the performance of the economy, and have a direct and long-term impact on the company. Social factors thoroughly examine the market's social environment and weigh the determinants of cultural trends and demographic analysis. Technical factors refer to technological advancements that may have a positive or negative influence on industry and market operations. There are two aspects of legal factors, which are external and internal. Various regulations in certain nations have an impact on the business environment, and companies retain their own rules. These two views were examined in legal analysis, and methods were then developed based on these legislations. For instance, labour law, safety standards, consumer law, etc. Lastly, environmental factors include all factors that influence or are influenced by the environment.

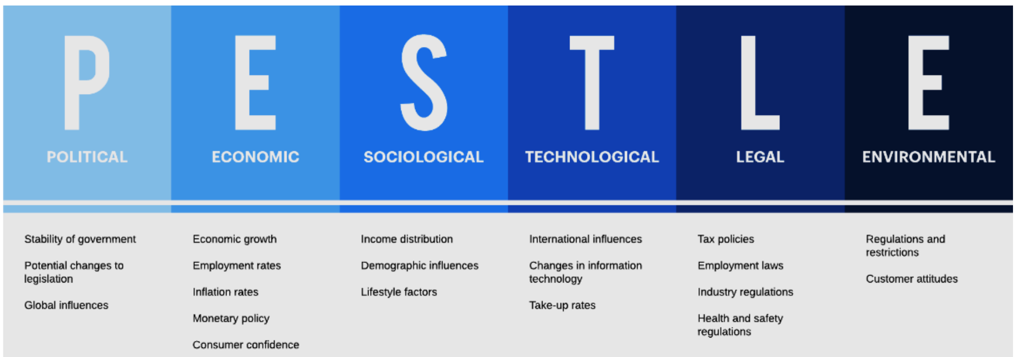


Figure 3.3: PESTLE Analysis (ECMS,2020).

3.4.4 Future Development of AI in Environmental Pollution

According to the results of SWOT analysis and PESTLE analysis, the future trend of AI system application in environmental pollution is proposed. Since SWOT analysis is able to find the problems and possible challenges, thus improvements or mitigation measures to current practices can be proposed. PESTLE analysis can identify key research areas of AI in the sector of environmental pollution and allows suggestions for any new developments in artificial intelligence in this field.

3.5 Summary

This chapter discussed the research methodology approaches used to conduct the study. Moreover, the procedures for collecting data in the literature review process and SWOT and PESTLE analysis were explained in this section. Proposal for future trends of AI application in environmental pollution was made according to results of analysis from SWOT and PESTLE Analysis. Lastly, a more detailed SWOT and PESTLE analysis as well as future development about AI in this field will be discussed in Chapter 4.

CHAPTER 4

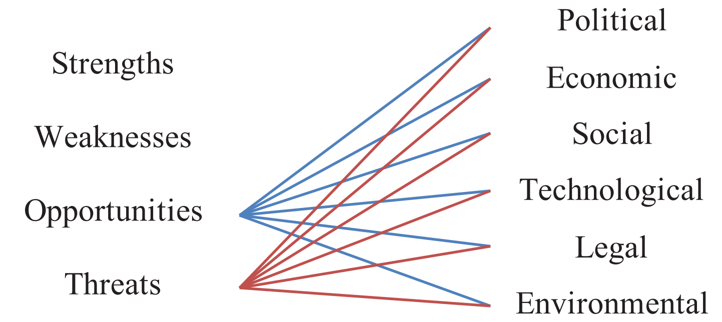
ANALYSIS AND DISCUSSION

4.1 Introduction

In this chapter, the results of the research were discussed by the SWOT analysis of AI application in environmental pollution. Although SWOT analysis considers both internal and external factors, a deep analysis of external factors are not performed. An extensive PESTLE analysis was conducted by using the finding in external factors in SWOT analysis (Freeman, 2021).

Table 4.1: Comparison between SWOT and PESTLE analysis (Freeman, 2021).

SWOT Analysis VS PESTLE Analysis



4.2 SWOT Analysis

The strengths, weaknesses, opportunities, and threats of utilising AI in environmental pollution will be analysed in this section. As mentioned in the chapter on methodology and working method, every SWOT Analysis element is analysed through the systematic literature review. Strengths are the contributions and outcomes of AI implementation in environmental pollution. The limitations and weaknesses of AI applications in environmental pollution are weaknesses. There are several areas where the implementation of AI can provide and improve work efficiency. These are the elements of opportunity in a SWOT analysis. Lastly, potential side effects and hazards that affect environmental pollution performance and operations are threatening factors. Table 4.2 shows a summary of the SWOT analysis for AI in environmental pollution.

Table 4.2: SWOT Analysis of AI Applications in the Environmental Pollution.

Strengths	Weaknesses
1. Increase workplace productivity and reduce operating costs (Soni, 2018). 2. AI model has a fabulous predictive ability (Ay and Özyıldırım, 2018). 3. AI model can manage missing values or incomplete databases. 4. AI models can monitor environmental conditions continuously (Yetilmezsoy, Ozkaya, and Caksmakci, 2011). 5. AI can act as a management tool for policymaking and decision-making (Djeddou, Hameed, and Mokhtari, 2019).	1. Cost and maintenance (Mullan, 2018). 2. Neural network development requires more computational resources and time (Blum, 1992). 3. Neural network models are prone to overfitting (Karul et al., 2000). 4. Unexplainable behaviour (Tu, 1996). 5. AI systems trained with biased data will affect the decision-making process (Adixon, 2019).
Opportunities	**Threats**
1. Many-objective optimization (Russell, 2016). 2. Open route to standardisation (Bridgwater, 2019). 3. AI-based technologies can be developed more in the decision-making sector (Hadjimichael et al., 2016). 4. Utilized DL and RL (MSV, 2018).	1. Potential job losses due to AI technologies (Risse, 2019). 2. Time and energy limitations (Fu, 2018). 3. Lack of data to train the AI model (Fu, 2018). 4. Technical threat (Baldassarre, Santucci, Cartoni, & Caligiore, 2017; Edwards, 2018).

4.2.1 Strengths

In Chapter 2, the Literature review, the potential applications and concepts of AI in environmental pollution have been reviewed. Undeniably, AI has the ability to expedite global efforts to safeguard the environment and conserve resources by detecting energy emission reductions and CO_2 removal, assisting in the development of cleaner transportation networks, monitoring deforestation, and anticipating extreme weather events (Mulhern, 2021).

With artificial intelligence, companies have a new way of thinking about improving internal processes, processing large quantities of data, and developing solutions that are sustainable for the long term. A decade of technological investment in water and wastewater operations will be driven by AI. According to Nelson (2020), water and wastewater businesses are investing in AI. According to a recent industry analysis, AI investments will reach $6.3 billion by 2030. The investment is part of a rising trend in the water sector to use smart infrastructure technologies to "go digital".

First and famous, First, AI technology is able to forecast and predict the data accurately. As discussed in chapter 2, water quality variables are often measured at unsystematic intervals, and the time series are usually short. There are many missing data in the dataset and long intervals with no measurements. As a result, water quality data are the most challenging hydrological data to assess using traditional hydrological methods. Therefore, AI technology has been proposed as an alternative to solve such problems. AI approaches, for example, have been effectively utilised to estimate silt in a river's breadth section, evaporation and evapotranspiration, rainfall-runoff, streamflow, water quality factors, and dam or lake water level modelling (Ay and Ozyldrm, 2018). The future level values using the ANNs technique, for example, were calculated using the river's historical level data (Li et al., 2016). According to Olyaie, Abyaneh, and Mehr (2017), four AI models were used to predict DO content in the Delaware River. RBF, MLP, SVM and LGP were the four AI models used in this study to examine their effectiveness. As a result, all AI models were able to retain their forecast accuracy even when the DO content was less. This study concludes that the AI model has a fabulous predictive ability.

Moreover, AI tends to increase productivity in the workplace. Employees can program artificial intelligence to work on tedious tasks instead of wasting hours on small, repeatable tasks. Besides that, it can also reduce the operating cost. Monitoring and consistency of measurements, as well as laboratory work, are both demanding and expensive instruments for assessing water quality. There is various research, for example, on techniques based on forecasting hydrologic variables using AI from data in sites where measurements are unavailable (Cibin et al., 2014; Waseem et al., 2015). In the noise pollution control sector, noise monitoring often involves the use of phonometers, which are professional and expensive instruments. Due to phonometers needing to be operated by humans, thus periodic fine-granularity city-wide observations are costly. Thus, low-cost sound pressure sensors are an alternative to perform the work. However, compared with phonometers, low-cost sound pressure sensors are not accurate and have great variability in measurement. In a study, Monti et al. (2020) used AI techniques to increase the accuracy of low-cost sound pressure sensors. The results showed that low-cost unattended noise monitoring throughout the city is workable.

On the other hand, AI is able to manage missing values or incomplete databases. Missing data always makes the analysis more difficult and sometimes impossible to analyze. Therefore, it is necessary to best use some contemporary machine learning models to impute missing data. Machine learning models like ANN have evolved from how the human brain works for classification, recognition, and recognition. According to the study by Sharma and Yuden (2021), missing data in rainfall and temperature have been imputed using kNN models and tree-based models. These imputed data have subsequently been used as predictors to predict river flow data using ANN. Here, the neural network is developed using the neural network R package developed by Fritsch et al. Predict the traffic of Uzorong and Muktirap stations with different input vectors. A logistic activation function with the backpropagation option was used when running the ANN model.

AI models are able to monitor environmental conditions continuously. Due to the dynamic nature of air, fluctuating, and high spatial and temporal variability of pollutants and particulate matter, the prediction has become a difficult task. At the same time, because of the severe effects of air pollution on communities and the environment, the capacity to analyse, predict, and monitor air quality is becoming increasingly vital, especially in metropolitan areas. In the air pollution control sector, Castelli et al. (2020) utilized SVR to monitor and forecast pollutants and particulate matter levels and identify AQIs correctly. The method studied yielded a suitable hourly air pollution model that allowed us to predict pollutant concentrations such as O^3, CO, and SO_2, as well as hourly AQI, with high precision.

In the soil and land pollution sector, AI is able to act as a management tool for policymaking and decision-making. Proper land management can help to prevent soil erosion. In environmental protection, flood management, forestry and agriculture, high-resolution soil feature maps are considered the most important input for making decisions. For example, Djeddou, Hameed, and Mokhtari (2019) created an ANFIS model to predict soil erosion in a fairly broad watershed with a limited number of input variables in the study. In this study, an accurate erosion risk map was generated to effectively manage the watershed in the long term. Besides that, field soil study and measurement are time-consuming and costly, as well as their application in a large area is limited. ANN can be used to forecast high-resolution soil organic content, soil drainage classes, and soil texture over a landscape with reasonable accuracy and minimal cost (Zhao et al., 2018).

4.2.2 Weaknesses

Although the application of AI and ML techniques is powerful, bringing us benefits and conveniences as discussed previously, there are still some weaknesses of AI in the environmental pollution needed to be focused on.

First, as with any form of new technology, it is expensive to purchase and requires ongoing maintenance and repairs. In addition, A.I. software may also require periodic upgrades to adapt to changing business environments (Mullan, 2018). For example, in the fields of environmental protection, flood management, forestry and agriculture, high-resolution soil feature maps are regarded as the most important input for decision-making and decision-making. In order to promote the diversification of forest land management methods, large-scale forest attribute maps are usually required (Moisen and Frescino, 2002). Therefore, the existing model needs to be updated whenever data is available in the future.

Furthermore, neural network modelling requires more computational resources. The construction of a neural network model is a time-consuming and computationally complex procedure. According to Le et al. (2019), AI techniques such as DT, SVM, and MLP networks do not work well on small training datasets. When the size of the dataset is small, the accuracy decreases. For example, a dataset with little variation can yield different DTs. It might take hours, days, or even weeks for a network to converge to an ideal learning state with minimum error using typical personal computer hardware and backpropagation techniques (Blum, 1992). For example, Olyaie, Abyaneh, and Mehr (2017) examined the effectiveness of four AI models in predicting DO content. The results show that SVM could provide the best accurate forecast of DO concentration. The reason why the prediction accuracy of the SVM model is better than other models is mainly due to the shortcomings of the model. For example, slow learning speed, overfitting, the curse of dimensionality and convergence to local minima.

Neural network models are prone to overfitting, which can affect the accuracy of the results. For example, any function may be approximated by a three-layer feedforward BP neural network with a sufficient number of neurons in the hidden layers. Therefore, it's important to be mindful that neural networks may memorise existing data rather than generalise to it, a phenomenon known as data overfitting. Overfitted neural network models frequently successfully duplicate the data in the training set but provide inaccurate estimates for data not in the training set (Karul et al., 2000).

Moreover, the black-box nature of ANN limits their ability to unambiguously identify possible causal relationships (Tu, 1996). Also, due to its unexplainable behaviour, when an ANN offers a probing solution, it does not explain why or how it works. This has a negative impact on network trust (Mijwel, 2018). As mentioned earlier, ANN consists of multiple layers. At the initial hierarchy level, the network learns some basic things. The data will then be forwarded to the next level, where it will be integrated into something more complicated. The process repeats itself, with each level building on the preceding level's input. However, the deeper the layer, the more difficult it is to optimize the algorithm. They eventually get so complicated that data scientists are unable to describe how and why they function. AI allows machines to make predictions, but it is difficult for computers to explain how decisions are made (Fu, 2018).

A big problem with AI systems is how good or bad they depend on the amount of data they are trained on. Bad data is often related to bias. If the bias buried in the algorithms that make key judgments remains unnoticed, unethical and unequal results might result (Adixon, 2019).

4.2.3 Opportunities

The advantages and limitations of applying AI and ML techniques in several components of environmental pollution were examined in the previous chapters. However, several potential areas of contribution can be further investigated for application to improve the quality of these techniques. There are several opportunities or favourable external factors that, if acted appropriately, may yield returns.

First and famous, different ethical concepts necessitate AI systems that are consistent with human values on a broad level (Blumenstock, 2018). As a result, the task is to create systems that optimise these values (Russell, 2016). Many-objective optimization utilising evolutionary algorithms can be a good place to start when it comes to broadening the scope of value realisation in AI systems. Many-objective optimization employs evolutionary computing approaches to produce alternatives for complicated planning issues, allowing for identifying critical trade-offs between decision parameters (Kasprzyk et al., 2013). This method is particularly well suited to multidimensional and unpredictable design processes, which abound in the water sector. Water supply (Kasprzyk et al., 2013), urban stormwater runoff (di Pierro et al., 2006), and water quality management (Chatterjee et al., 2017) are some of the topics highlighted. According to a study of water allocation in the Lower Rio Grande Valley of Texas, the use of many-objective optimization resulted in water management methods that were more sensitive to water shortage situations. In contrast, standard optimization approaches would not be deemed successful. Promising (Kasprzyk et al. 2016). On the other hand, uncertainty does not just apply to climatic and demographic situations but also to human values. As a result, the true difficulty is building AI algorithms that are flexible in terms of optimising values rather than pre-optimising for specified values (Van de Poel, 2018).

This sketch depicts the water sector's potential for AI-based solutions. Many applications focusing on the optimal design of water distribution networks exist in terms of design and planning. Many of the techniques outlined in academic studies have also been used in real-life situations (Van Thienen et al., 2018). Hadjimichael et al. (2016) find that only a tiny portion of the academic literature on ML and water covers decision-making, implying that water lags behind generally related industries such as energy and logistics in this regard (Van Thienen, 2019). As a result, AI-based solutions in the decision-making industry can be further developed.

The next generation of AI might be influenced by open-source technology. This is because the open model of shared codebases based on community contributions has become the de facto approach for any technology to achieve widespread standardisation on its way to becoming viral. Furthermore, it is critical to refine, supplement, extend, model, construct and debug AI systems in an open-source environment, where the combined mass work of whole software communities may assist in making AI systems smarter (Bridgwater, 2019).

Next is the advancement in DL and ANN. DL and ANN can be utilized and replaced with the traditional techniques to evolve accurate and precise versions. CNN, as previously stated, enables deep learning capabilities for visual monitoring. Image processing is being discovered thanks to advancements in computer vision such as the Single Shot Multibox Detector (SSD) and Generative Adversarial Networks (GANs). Emerging machine learning technologies like CapsNet (CapsNet) will also affect how ML versions are distributed and taught. Even with little data for training, they can create models that forecast reliably (MSV, 2018). In this scenario, it will undoubtedly improve the environmental contamination industry, as existing AI applications frequently need a large quantity of data in order to achieve reliable results. For example, in a tumultuous environment, the current cognitive technique is used to detect an unknown emitting source. The high computing cost of cognitive techniques, on the other hand, limits their use in real-world search and rescue efforts. In order to learn an efficient policy for source seeking, reinforcement learning (RL) can be used. The learnt policy is computationally efficient, resulting in a quick decision-making process (Zhu et al., 2021).

4.2.4 Threats

While the application of AI benefits humans in terms of quality of life, productivity, and convenience of daily activities, there are still potential threats to these modern technologies. Although AI has many applications in the field of environmental pollution, some external factors or obstacles may hinder the desired achievement. These threats must be identified and made aware to prevent malicious attacks and exploit the prevalence of these advanced technologies.

The first is a social threat. Some of the research looked at the societal implications of probable employment losses due to AI. This matter has garnered a lot of attention in the media and is being discussed in a lot of places. According to Risse (2019), AI poses issues for humans, affecting the nature of labour and perhaps influencing people's standing as members of society. As part of an integrated AI and human-centric workforce, human employees are anticipated to rise up the value chain, focusing on using human qualities to address design and integration difficulties (DIN & DKE, 2018; Jonsson & Svensson, 2016; Makridakis, 2018; Wang, Törngren, & Onori, 2015; Wang, Li, & Leung, 2015; Wang & Wang, 2016).

Time and energy limitations may also limit the applications of AI in environmental pollution. Undeniably, the main focus of AI is to create robust algorithms. However, many do not realise that not every system is designed to deploy AI solutions effectively. It is a problem that is frequently overlooked. Furthermore, there are also storage challenges (Fu, 2018).

Moreover, environmental pollution still suffers from a lack of data to train the AI model. In fact, the success of AI and its prediction accuracy strongly depends on the availability of quality training data to develop models that give meaningful learning and results. AI models cannot be created without a certain quantity of data, just like the human brain, that requires information to develop

(Fu, 2018). For instance, it is hard to forecast the outcomes of a rare environmental condition because there are only a few datasets to pull from. Due to the lack of adequate training data, many activities will remain unrecognisable. According to Luo et al. (2018), the lack of an available database is a significant challenge that can impede the creation of action analysis using computer vision. However, massive data could lead to data privacy and security issues. The AI applications for environmental pollution depend on a large amount of data to learn and make smart decisions.

Next is the technological threat. The non-boolean nature of diagnostic activities in the environment has been studied and the difficulties of applying AI technology to data and image interpretation. Humans use cautious language or descriptive terms, not only binary language, according to Tizhoosh and Pantanowitz (2018), but AI-based systems tend to operate as a black box, with the lack of transparency acting as a barrier to adoption. For example, there are risks associated with AI system architecture and the necessity for complex frameworks to comprehend human cognitive flexibility, learning speed, and even moral traits (Baldassarre, Santucci, Cartoni, & Caligiore, 2017; Edwards, 2018). The technological issues of algorithm opacity and the inability to comprehend unstructured data were discussed by Sun and Medaglia (2019). Machine learning algorithms should be developed by machine learning experts who have a thorough grasp of the environment and the potential outcomes and repercussions. Mitchell (2019) stated that artificial intelligence systems do not yet possess the essence of human intelligence. AI systems are unable to comprehend human events and draw the appropriate meaning from them. This semantic barrier renders present AI systems vulnerable in a variety of ways, but especially to hacker assaults known as "adversarial instances." A hacker can make specific and minor alterations to sound, picture, or text files in these assaults, which will not affect human cognition but may lead a computer to commit potentially catastrophic errors (Mitchell, 2019).

4.3 SWOT Analysis Summary

After analysing each SWOT analysis element, this section tabulates and classifies the SWOT according to different AI applications in environmental pollution.

4.3.1 Water and Wastewater Management

Table 4.3 illustrates the SWOT analysis of Water and Wastewater Management in environmental pollution. As mentioned in Table 4.3, the main strength of AI application in water and wastewater management is that AI is able to select the essential input variables for accurate modelling (Ay and Özyıldırım, 2018). It is believed that the development of AI in water and wastewater management is able to minimise water system expenses and pollution. However, every AI technique application has its limitation. For example, the high temporal variability of water-related processes such as bacterial estimation is a challenge for AI modelling (Palomares, 2021). Besides, the wide range of AI technologies makes it difficult to select the most suited one, especially considering the scarcity of people that are both AI and water resource specialists.

Table 4.3: SWOT Analysis of AI Applications in Water and Wastewater Management

Strength	Weakness
1. ANNs provide a robust tool for prediction (Ozkaya et. al., 2008). 2. Selecting the most essential input variables; selecting the most essential input variables for accurate modelling (Ay and Özyıldırım, 2018). 3. A robust and effective control and management system (Hamed, Khalafallah, and Hassanien, 2004).	1. Restricted to investigating correlations between variables of interest rather than taking into account later responses to outcomes (Nishant, Kennedy, and Corbett, 2020). 2. The high temporal variability of water-related processes such as bacterial estimation is a challenge for AI modelling (Palomares, 2021).

Table 4.3 (Continued)

4. ANNs as a pattern recognition technique (Onkal-Engin, Demir and Engin, 2005).	3. Inability to learn water management models due to a lack of high-quality data and accurate information (Palomares, 2021). 4. The focus on short-term forecasting models ignores advances in long-term reliable water forecasting (Palomares, 2021).
Opportunity	Threat
1. ML can focus on decision making (Hadjimichael et al. 2016) 2. Analyzing a large quantity of past data to forecast future failures in water infrastructure (Palomares, 2021). 3. Accurate AI approaches to minimise water system expenses and pollution (Palomares, 2021).	1. The diversity of AI technologies presents challenges in choosing the most appropriate technology, especially given the lack of joint expertise in AI and water resources (Palomares, 2021). 2. AI application creates a huge carbon footprint (Hao, 2019).

4.3.2 Air Pollution Control

As mentioned in Chapter 2, predicting air quality is difficult due to the volatility and dynamics of pollutants and particulate matter and the extreme unpredictability of time and place. Thus, it must be continuously monitored and appropriately controlled. According to Yetilmezsoy, Ozkaya, and Caksmakci (2011), the AI model is able to monitor and record the data continuously. Therefore, the human workforce can be reduced. In contrast, there is no one AI-based approach to identify all important geographic scales of air pollution events. Table 4.4 shows the SWOT analysis of the applications of AI in air pollution control.

Table 4.4: SWOT Analysis of AI Applications in Air Pollution Control

Strength	Weakness
1. Predictive machine learning is invaluable for air quality prediction and analysis tasks (Palomares, 2021). 2. Able to monitor and record data continuously (Yetilmezsoy, Ozkaya, and Caksmakci, 2011). 3. Reduce the human workforce (Soni, 2018).	1. No one AI-based approach is capable of identifying all important geographic scales of air pollution events (local, regional and global) (Anand, 2020).
Opportunity	**Threat**
1. An AI enabler to aid in the reduction of air pollution. It can aid in the better measurement, identification of causes, formulation of policies, prediction, forecasting, and application of logic to issues (Anand, 2020).	1. Ethical AI conundrums around "whom to blame" for catastrophic choice results (Palomares, 2021).

Table 4.4 (Continued)

2. Educating employees on how to use reliable AI to make better decisions (Palomares, 2021). 3. AI can deliver actionable information, such as daily updates and suggestions on air quality levels along their commute (Anand, 2020)	

4.3.3 Noise Pollution Control

Phonometer is a professional and costly device in noise monitoring, which is able to measure sound pressure levels accurately. Periodic fine-grained city-wide observations are costly as phonometers require manual operation. With the assistance of AI techniques, a low-cost sound pressure sensor is able to measure the sound pressure levels accurately, thus reducing the operating cost (Monti et al., 2020). At the same time, the application's weakness is that the noise can only be evaluated at one receiving point. The SWOT Analysis of AI application in noise pollution control is summarised in Table 4.5.

Table 4.5: SWOT Analysis of AI Applications in Noise Pollution Control

Strength	Weakness
1. Predicting accurately and enhancing efficiency in the workplace (Choi et al., 2021).	1. Evaluate noise at only one single receiving point (Han, 2017).
2. Improve the quality of life of workers (Hong et al., 2021).	2. ANN requires a large amount of historical data for training (Shanmuganathan, 2016).

Table 4.5 (Continued)

3. A great contribution to optimizing the overall cost (Hong et al., 2015). 4. Increase accuracy of low-cost sound pressure sensors (Monti et al., 2020) 5. AI is able to reduce the cost with a combination of low-cost sensors (Monti et al., 2020).	
Opportunity	Threat
1. Compared to traditional models, researchers have the option of including more associated characteristics in the noise prediction modelling process. (Mansourkhaki, 2018)	1. The lack of noise-related data (Lim, 2017)

4.3.4 Soil and Land Pollution

Soil erosion has become a major challenge for sustainable livelihoods around the world. Soil erosion is a process that involves the separation, movement and consolidation of eroded soil particles on or off-site. With the assistance of AI techniques, high-resolution maps are able to be generated with reasonable accuracy and minimal cost. This can also technically reduce the human workforce's involvement. However, ensuring the workability of wireless sensors in a challenging environment is difficult. Table 4.6 shows the SWOT Analysis of the implementation of AI in Soil and Land pollution.

Table 4.6: SWOT Analysis of AI Applications in Soil and Land Pollution

Strength	Weakness
1. ANN models are able to generate high-resolution maps of soil properties in conjunction with satellite data to forecast soil organic content, soil drainage classes, and soil texture over a landscape (Zhao et al., 2018). 2. Classification of land and soil is a non-intrusive process. 3. AI techniques such as ANN and Decision Trees will provide judgements, decisions, and improvement schemes (Liakos, et al., 2018; Charania and Li, 2020).	1. Wireless sensors can be damaged, blocked or interfered with by a challenging environment (Aqeel-Ur-Rehman, et al., 2014). 2. Erosion prediction necessitates accurate real-time data, which is out of reach in some areas (Palomares, 2021). 3. Black-box AI models are difficult to use by emergency services to justify decisions against disasters (Palomares, 2021).

Table 4.6 (Continued)

Opportunity	Threat
1. Early warning of natural disasters allows authorities to respond quickly to minimise damages (Palomares, 2021).	1. Invasive smart sensors will be broken or damaged easily due to external conditions or human-made damage (Aqeel-Ur-Rehman, et al., 2014).
2. New technologies for drones can technically reduce the human workforce's involvement (Castelló Ferrer, et. al., 2017).	2. The result of smart sensors' analysis from the data collected will be affected by noise (Saiz-Rubio and Rovira-Más, 2020)

4.4 PESTLE Analysis

In this section, PESTLE analysis will be conducted by discussing the AI applications in environmental pollution. As the scope and depth of potential applications increase and the use of AI become more mainstream, the implementation of AI technologies could have important political, economic, sociological, technological, legal, and environmental impacts. Table 4.7 summarizes the PESTLE analyses discussed in this section.

Table 4.7: Summary of PESTLE Analysis

PESTLE Factors	Summary
Political	• AI can be a threat to democratic institutions (Hao, 2019). • Bias is hidden in data (Vinuesa, 2020). • AI can also assist government sectors in increasing the efficiency of work (Corvalán, 2018).
Economic	• AI could double the annual growth rate of the global economy by 2035 (Szczepanski, 2019). • Substantial increases in labour productivity (Szczepanski, 2019). • The economic gap may be significantly increased (Acemoglu and Restrepo, 2018). • Advancements in A.I. will increase the unemployment rate (Dutton, 2018).
Sociological	• Improve the efficiency of our workplaces (Soni, 2018). • Enhance the jobs humans can do (Soni, 2018). • Reduce Human errors (Soni, 2018). • Potential job losses (Rory, 2014). • Wealth inequality (Rory, 2014).
Technological	• Lack of transparency and the "Black box" nature of AI (Tizhoosh and Pantanowitz, 2018). • Non-Boolean nature (Tizhoosh and Pantanowitz, 2018).

Table 4.7 (Continued)

	• Security needs to be integrated starting from the product concept throughout the entire lifecycle (Neustadter, 2020).
Legal	• Most countries have few AI laws and regulations (Cognilytica, 2021). • Laws are border on data privacy and protection (Cognilytica, 2021). • Applications that may violate fundamental rights and some high-risk applications of AI are prohibited. (EC, 2021).
Environmental	• AI can act as an enabler (Vinuesa, et al., 2020). • AI can also be used to help improve the health of ecosystems (Albaradeyia, Hani, and Shahrour, 2010) • AI is being applied to improve biodiversity monitoring and conservation (Silvestro, Goria, Sterner and Antonelli, 2022).

4.4.1 Politic Factor

The majority of incidents suggest that AI can pose a danger to democratic systems (Hao, 2019). These dangers can include everything from data collection and privacy breaches to election hacking, among other things. For example, using Facebook as a propaganda platform through its machine learning and algorithms is well-known among fanatics and hobbyists. Since President Rodrigo Duterte's victory in 2016, there has been an explosion of fake news and profiles on Facebook. Another example is Facebook ads that almost "match" the personality of the person they're targeting.

AI can have a detrimental influence on social media usage by providing people with material that is tailored to their preconceived notions. This might lead to political polarisation and a deterioration of social cohesiveness, with negative implications for decreasing disparities. On the other hand, AI may assist in identifying and perhaps reducing the roots of inequality and conflict, such as by utilising simulations to examine how virtual communities respond to change. However, utilising AI to analyse and forecast human behaviour carries a danger of data bias. The use of artificial intelligence to automatically target online job adverts is said to provide a variety of discriminatory issues, particularly relating to selection bias by human recruiters. For this reason, Dalenberg's study underscores the necessity to improve data preparation and specifically change AI-based algorithms utilised for selection (Vinuesa, 2020).

AI is here to stay whether users like it or not. It will also make waves politically for years to come. Existing laws and regulations may be strengthened with additional protections to better protect users on platforms that incorporate AI technologies. Nonetheless, there are at least some measures in place to ensure that a company's external data use complies with the law.

While there may be concerns about the application of AI, there is no denying that it can help solidify institutions, procedures (in government or otherwise), cultures and ideologies. When used properly, AI can ease the administrative burden. AI can also assist government sectors in increasing the efficiency of work as well (Corvalán, 2018). The assistance of AI will help ensure the safety of a city's government and financial system. Other than that, the citizens' well-being can be increased by AI's assistance in making appropriate regulations for the city.

4.4.2 Economic Factor

In terms of required investment and changes in working patterns, the mass adoption of AI technology could have a big economic impact on organisations and institutions.

The majority of research claim that AI will have a big economic impact. According to a research sponsored by a consulting firm, Accenture and involving 12 globalised economies, AI could double the global economy's yearly growth rate by the year 2035, which is able to create more than 0.5 per cent of global economic output. AI will drive this growth in three main ways. First, it will result in huge gains in labour productivity, which is up to 40%. This is because new technology enables more effective labour-related time management. Second, AI will give rise to a new type of virtual labour known as "intelligent automation," which has the ability for self-learning and problem-solving. Third, the economy will profit from the spread of innovations, which will have an influence on a wide range of industries and provide new revenue streams (Szczepanski, 2019).

Although Acemoglu and Restrepo (2018) claim that AI technology has a net beneficial influence in terms of higher productivity, the literature also highlights possible negative consequences, particularly in terms of greater inequalities. If future markets are heavily reliant on data analysis, and these resources are not evenly available in low- and middle-income nations, the economic gap might widen dramatically as a result of newly imposed inequities.

According to Brynjolfsson and McAfee (2014), AI can aggravate inequality inside countries as well. Technology disproportionately compensates the educated by replacing old professions with new ones that need more skills: since the mid-1970s, earnings in the United States (US) have increased by around 25 per cent for those with graduate degrees, while the average high-school dropout has seen a 30 per cent reduction in pay. Furthermore, automation shifts corporate income to those who own companies from those who work there. Even though the combined revenues of Detroit's "Big 3" (GM, Ford, and Chrysler) in 1990 were almost identical to those of Silicon Valley's "Big 3" (Google, Apple, and Facebook) in 2014, the latter had nine times fewer employees and were worth 30 times more on the stock market due to this transfer of revenue from workers to investors.

Besides, advancements in AI will increase the unemployment rate. As a result, in order to ensure that workers have the skills they need to compete in the digital economy, the government must invest in STEM education, national retraining programmes, and lifelong learning (Dutton, 2018).

4.4.3 Sociological Factor

AI has the potential to drastically increase the efficiency of our workplaces while also enhancing the occupations that people can perform. When artificial intelligence (AI) takes over monotonous or risky duties, it frees humans to focus on their more capable vocations, such as creativity and empathy (Soni, 2018). People's well-being and job satisfaction may improve if they work in more appealing jobs.

Besides that, the human mistake in the workplace is unavoidable and frequently costly; the higher the level of exhaustion, the greater the danger of errors. On the other hand, technology does not suffer from tiredness and emotional distraction. It reduces mistakes and allows people to do the task more quickly and precisely. With better monitoring and diagnostic capabilities, AI can greatly impact the field of environmental pollution. Humans will be free to spend their time in a number of various ways now that they are no longer bound by uncomfortable commutes (Soni, 2018).

Studies have also looked at the societal implications of potential employment losses due to AI. This matter has garnered a lot of attention in the media and is being discussed in a lot of places. This is because many works will be replaced by machinery. Nowadays, many vehicle assembly lines are now dominated by equipment and robots, displacing conventional employees. Clerks are no longer required in supermarkets, as automated technologies may replace physical labour (Rory, 2014). According to Risse (2019), AI poses issues for humans, affecting the nature of labour and perhaps influencing people's status as people in society. As part of an integrated AI and human-centric workforce, human employees are anticipated to rise up the value chain, focusing on using human characteristics to address design and integration difficulties (DIN & DKE, 2018; Jonsson & Svensson, 2016; Makridakis, 2018; Wang, Törngren, & Onori, 2015; Wang, Li, & Leung, 2015; Wang & Wang, 2016).

Because AI investors will pick up most of the earnings, wealth disparity will be generated. The wealth divide between rich and poor will increase. The so-called “M” shape wealth distribution will be more obvious (Rory, 2014). According to Ohmae's concept of M-shape society, income distribution is no longer regular but rather M-shape. The wealthy become wealthier, the poor become poorer, and the middle class becomes further polarised (Ohmae, 2006).

4.4.4 Technological Factor

Some stakeholders point to perceived concerns related to AI technology' nature and characteristics. These technological problems include AI algorithms' lack of transparency and the AI system's difficulty handling unstructured data. This lack of transparency is seen as a key barrier; AI technology is viewed as a "black box," with users having no capacity to comprehend or adjust its procedures to address possible issues.

Another study analyzes the non-Boolean nature of diagnostic tasks and the challenges of applying AI techniques to data and imaging interpretation. Tizhoosh and Pantanowitz (2018) highlight that humans use discreet language or descriptive terms, not just as a function of a black-box but also as a binary language. These views were reinforced by Cleophas and Cleophas (2010) and Kahn and Winters (2017), which identified some limitations of AI in imaging and diagnostic tasks.

AI is frequently used to analyse extremely sensitive data in areas such as environmental pollution, healthcare, and more. As a result, having this information leaked would be disastrous for an organization. Furthermore, improper data injection might cause AI systems to form incorrect conclusions, resulting in incorrect judgments (Kerravala, 2018). Therefore, A secure boot loader is an example of an underlying security feature that checks to see if a product's software or firmware is in good working order (has integrity). After the product leaves the reset, integrity assures that the product performs the creator's purpose, not what a hacker altered. In addition, the Secure Boot mechanism verifies the firmware's validity using a cryptographic signature. It is indisputable that AI applications will continue to grow in complexity, requiring data and models to be updated regularly. The whole process of securely disseminating new models must be protected. As a result, it's crucial to securely update the product to fix issues, shut bugs, and improve product functioning (Neustadter, 2020).

4.4.5 Legal Factor

In the field of legal research, despite the apparent rapid development and adoption of AI technology globally, most countries have failed to develop and implement relevant regulations for the use of AI in parallel. Cognilytica (2021) report shows that most countries have few AI laws and regulations. Even in countries where these laws exist, they mostly border on data privacy and protection. While other equally important areas are not taken seriously, such as autonomous decision-making, facial recognition, dialogue systems, malicious

AI use, AI ethics and bias, and the oft-argued Issues of AI legal personality and liability (Cognilytica, 2021).

While the U.S. is a world leader in AI, it appears to be taking a laid-back democratic approach to AI regulation. While there is no comprehensive federal law on AI use, some states have enacted their own (Broadbent and Arrieta-Kenna, 2021). Some argue that the U.S. approach has created a favourable environment for AI research and development. This is in stark contrast to the Chinese government's outsized authoritarian interest in AI research and applications (Broadbent and Arrieta-Kenna, 2021). Globally, the EU has the most comprehensive and coordinated AI regulatory framework (Cognilytica, 2021), prohibiting some applications of AI (for example, applications that may violate fundamental rights), and severely restricting some high-risk applications of AI (For example, systems are used as safety components), and other components considered low risk are lightly regulated (EC, 2021).

4.4.6 Environmental Factor

AI can act as an enabler. The benefits of AI can be obtained through the possibility of analysing large interconnected databases to formulate joint actions aimed at protecting the environment (Vinuesa, et al., 2020). As discussed previously, there is evidence that AI advances are able to support the understanding of environmental change and the modelling of its possible impacts so that humans can effectively prevent or avoid disasters.

Furthermore, AI will aid low-carbon energy systems that have a high level of renewable energy and energy efficiency, all of which are necessary to combat climate change. AI may potentially be utilised to assist and enhance ecological health. For example, Albaradeyia, Hani, and Shahrour (2010) introduced ANN for soil loss and runoff prediction to combat soil erosion and restore degraded land and soil.

Research by Zhao et al. (2018), ANN and ML can be used to generate high-resolution maps of soil properties, with the ability to analyse vast quantities of pictures in a short period of time. These AI techniques can assist in identifying desertification and soil erosion trends over large areas, which is useful information for environmental planning, decision-making, and management to prevent further desertification and soil erosion or reverse trends by identifying the major drivers.

Furthermore, while there are several examples of AI being used to promote biodiversity monitoring and conservation, it is possible that increased access to AI-related information in ecosystems may lead to resource overexploitation, despite this abuse not being adequately documented (Silvestro, Goria, Sterner and Antonelli, 2022).

4.5 Future Development of AI in Environmental Pollution

As shown in the literature review in the previous part, most of the research and study about AI application in the environmental sector are more focusing on forecasting and prediction. There are many fields yet to be explored, such as decision-making systems, etc. According to Li, Lam, and Cui (2021), AI can replace human beings in analyzing big data at high computational efficiency and precision and recovering missing data. These capabilities place AI in a much better position to perform complex environmental decision-making. Besides, AI can also autonomies information gathering and the process of decision-making. AI has the potential to vastly enhance environmental management systems, such as water and wastewater, solid and hazardous waste management, noise control and so on.

Apart from that, lack of transparency is perceived as a major challenge of AI. The “black box” model applied to design AI models concealed the design reasoning of the AI model. The transparency of the AI model design shall be lawfully regulated in the future. The incentives and limitations of all stakeholders involved should be considered and provide appropriate opportunities for feedback, relevant explanations, and appeal (Cowls et al., 2019). AI technologies should be appropriately guided and controlled by humans (Google, 2021). For example, ecosystem restoration is frequently a multi-disciplinary undertaking, including politicians, data scientists, earth scientists, and indigenous populations. Traditional ecological knowledge and data science methodologies must frequently be seamlessly integrated in order to produce successful machine learning applications.

AI algorithms and datasets should be developed to reflect or minimise unfair prejudices. They must be created using debiasing approaches to eliminate inequitable effects on people, such as prejudices based on race, ethnicity, gender, nationality, income, or political or religious beliefs (Google, 2021).

Additionally, AI developers should create open sources of data sources, algorithms, and sources of economic AI machines. This is because the cost of purchasing data for the training and operation of AI models can be high. The high initial cost will be one of the retention factors for the development of artificial intelligence in the field of environmental pollution. The initial cost of AI implementation in environmental pollution can be reduced by opening up resources. With open AI resources, researchers can save a lot of time from repeating work and gain more insight and detailed information about real-life environments.

4.6 Summary

In this chapter, the SWOT analysis of AI application in environmental pollution was discussed in detail. According to analysis, AI dramatically improves the efficiency of work. Over time, AI technology will continue to develop, and as computers become more widely used, there will be broad prospects in the environmental sector. However, the coin always has two sides. This chapter also outlines some of the weaknesses or limitations of current AI technology. Therefore, further research is still needed to overcome the limitations of AI implementation. There is still a lot of room for improvement in the future to produce robust and perfect models.

This chapter also discussed the PESTLE analysis of AI applications in the environmental sector in six different factors. Therefore, the reader can understand the detail of AI applications in the manufacturing industry from this analysis. In addition, the last part of this chapter is a discussion of AI applications that may be applied to environmental pollution in the future.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Introduction

This is the last chapter of the whole research. The accomplishment of the research objectives is reviewed in Section 5.2. The recommendations for further study are also included in this chapter in Section 5.3.

5.2 Accomplishment of Research Objectives

This research presented a brief introduction to the current AI development in environmental pollution. The first objective was to review the concepts of AI and environmental pollution. The literature regarding the concepts of environment, AI, and ML were reviewed. The environmental pollution being reviewed are water and wastewater treatment, air pollution control, noise pollution control and soil. This exploratory research method was carried out according to the flowchart shown in Figure 3.1. A total of 191 research journals have been reviewed to study the applications and issues of AI in environmental pollution. Therefore, by conducting the literature review on the applications of AI in environmental pollution, the concepts of AI and environmental pollution were captured. Thus, the first objective of this research is attained.

The second objective was to conduct the SWOT and PESTLE Analysis of the deployment of AI in environmental pollution. SWOT Analysis was conducted according to LR done in the previous chapter to determine the advantages, disadvantages, potential development, and potential harm of AI to the environmental sector in the future. It is undeniable that AI has made great contributions to environmental pollution, from data prediction to decision-making. While AI will bring countless benefits to the field of environmental pollution, some research journals point to problems arising from the social costs associated with potential job losses or the ethics of allowing AI to dictate safety protocols. Besides, some of the challenges or threats of AI have also been identified in this research, such as social threats, technological challenges, legal issues, and privacy and security problems concerning the AI applications.

The final objective of this research is to propose the future development of AI in environmental pollution. Proposal for future trends of the AI application was made according to analysis results from SWOT and PESTLE Analysis. PESTLE Analysis shows the mapping of four different fields in the environmental pollution in six different factors. Overall, as mentioned above, all three objectives of this study were successfully achieved.

5.3 Recommendations for Future Work

In this study, four of the environmental pollution fields have been studied and analysed. A more precise range will be defined in future research. It helps researchers focus on specific topics through precise research scope. In addition, this study also highlights some additional areas for future research, which include the environmental decision-making system. As mentioned above, most AI-based models focus on data forecasting and prediction instead of decision-making. Due to the time constraints, this study only managed to propose the future development of AI in environmental pollution without developing it. Future researchers can try to explore and collect more detailed information and collection technologies to develop a decision-making model.

As previously stated, the research is constrained by a lack of data access. As a result, future researchers should continue to investigate AI's applications in environmental pollution and look for ways to enhance present AI algorithms or technologies in order to boost the industry's efficiency even more.

Finally, the scope of this study can be expanded. The research direction of this paper only focuses on environmental pollution. However, real-world applications of AI are not just concerned with environmental pollution. This research can further discuss the broader scope, such as applying AI in environmental engineering.

REFERENCES

AAEES (The American Academy of Environmental Engineers and Scientists), n.d. *Careers in environmental engineering and environmental science*, *Aaees.org*. [online] Available at: < https://www.aaees.org/careers/ > [Accessed 10 August 2021]

Abbasi, M., Abduli, M.A., Omidvar, B. and Baghvand, A., 2013. Results uncertainty of support vector machine and hybrid of wavelet transform-support vector machine models for solid waste generation forecasting. *Environmental Progress & Sustainable Energy*, [e-journal] 33(1), pp.220–228. http://dx.doi.org/10.1002/ep.11747.

Abdallah, M. et al., 2020. Artificial intelligence applications in solid waste management: A systematic research review. *Waste Management*, 109, pp.231–246. http://dx.doi.org/10.1016/j.wasman.2020.04.057.

Acemoglu, D. and Restrepo, P., 2018. Artificial intelligence, automation, and work. *The economics of artificial intelligence: An agenda* [e-hournal] pp. 197-236. 10.3386/w24196

Adixon, R., 2019. Artificial Intelligence Opportunities & Challenges in Business. [online] Available at: < https://towardsdatascience.com/artificial-intelligence-opportunities-challenges-in-businesses-ede2e96ae935> [Accessed 11 March 2022].

Akkoyunlu A., Yetilmezsoy K., Erturk F., Oztemel E., 2010. A neural network-based approach for the prediction of urban SO2 concentrations in the Istanbul Metropolitan Area. *International Journal of Environment and Pollution*, [e-journal] 40(40), pp. 301-321. http://dx.doi.org/10.1504/IJEP.2010.031752

Akkurt S., Tayfur G., and Can S., 2004. Fuzzy logic model for the prediction of cement compressive strength. *Cement and Concrete Research*, [e-journal] 34(8), pp. 1429-1433. https://doi.org/10.1016/j.cemconres.2004.01.020

Albaradeyia, I., Hani, A. and Shahrour, I., 2010. WEPP and ANN models for simulating soil loss and runoff in a semi-arid Mediterranean region. *Environmental Monitoring and Assessment*, [e-journal] 180(1–4), pp.537–556. http://dx.doi.org/10.1007/s10661-010-1804-x.

Anand, M., 2020. *How Artificial Intelligence can help improve air quality*. [online] Available at: <https://yourstory.com/2020/08/artificial-intelligence-improve-air-quality/amp> [Accessed 28 March 2022].

Anaokar G.S., Khambete A. K, 2016. Application of Fuzzy Logic in Environmental Engineering for Determination of Air Quality Index, *International Journal of Engineering Technology, Management and Applied Sciences,* [e-journal] 4(2), pp. 109-116. Available at: < https://www.researchgate.net/publication/295909347_Application_of_Fuzzy_Logic_in_Environmental_Engineering_for_Determination_of_Air_Quality_Index?enrichId=rgreq-748fe0bcaf7836661145ed426bbc0393-XXX&enrichSource=Y292ZXJQYWdlOzI5NTkwOTM0NztBUzozMzMzNTQ1NjMwNjM4MTVAMTQ1NjQ4OTMyOTc2Mg%3D%3D&el=1_x_2&_esc=publicationCoverPdf> [Accessed 14 August 2021].

Aqeel-ur-Rehman, Abbasi, A.Z., Islam, N. and Shaikh, Z.A., 2014. A review of wireless sensors and networks' applications in agriculture. *Computer Standards & Interfaces*, [e-journal] 36(2), pp.263–270. http://dx.doi.org/10.1016/j.csi.2011.03.004.

ASCE (American Society of Civil Engineers), 1977. Statement of Purpose. *Official Record*, Environmental Engineering Division, American Society of Civil Engineers, New York.

ASCE (American Society of Civil Engineers), 2010. *Code of Ethics*. [online] Available at: < https://www.asce.org/code-of-ethics/ > [Accessed 10 August 2021].

Ay, M. and Özyıldırım, S., 2018. Artificial Intelligence (AI) Studies in Water Resources. *Natural and Engineering Sciences*, [e-journal] 3(2), pp.187–195. http://dx.doi.org/10.28978/nesciences.424674.

Baldassarre, G., Santucci, V.G., Cartoni, E. and Caligiore, D., 2017. The architecture challenge: Future artificial-intelligence systems will require sophisticated architectures, and knowledge of the brain might guide their construction. *Behavioral and Brain Sciences*, [e-journal] 40. http://dx.doi.org/10.1017/S0140525X17000036.

Baxter, C. W., Stanley, S. J. and Zhang, Q., 1999. Development of a full-scale artificial neural network model for the removal of natural organic matter by enhanced coagulation, *Aqua*, 48(4), pp. 129-136.

Blumenstock, J., 2018. Don't forget people in the use of big data for development. *Nature*. [e-journal] 561(7722), 170-172. https://doi.org/10.1038/d41586-018-06215-5

Bridgwater, A., 2019. *Key factors driving AI in 2020*. [online] Available at: <https://techhq.com/2019/12/key-factors-driving-ai-in-2020/> [Accessed 13 November 2020].

Broadbent, M., Arrieta-Kenna, S., 2021. *AI Regulation: Europe's Latest Proposal is a Wake-Up Call for the United States*. [online] Available at: < https://www.csis.org/analysis/ai-regulation-europes-latest-proposal-wake-call-united-states> [Accessed 11 April 2022].

Brynjolfsson, E. and McAfee, A., 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. [e-book] WW Norton & Company. Available at: Google Books < https://books.google.com.my/books?hl=en&lr=&id=WiKwAgAAQBAJ&oi=fnd&pg=PA1&dq=The+Second+Machine+Age:+Work,+Progress,+and+Prosperity+in+a+Time+of+Brilliant+Technologies&ots=4_XwXi4v9d&sig=GCjxTcQYXP0n46ACNFJg_WPSj5I#v=onepage&q=The%20Second%20Machine%20Age%3A%20Work%2C%20Progress%2C%20and%20Prosperity%20in%20a%20Time%20of%20Brilliant%20Technologies&f=false > [Accessed 11 April 2022]

Bujan, A., Santanatoglia, O. J., Chagas, C., Massobrio, M., Castiglioni, M., Yanez, M. S., et al., 2000. Preliminary study on the use of the 137Cs method for soil erosion investigation in the Pampean region of Argentina. *Acta Geologica Hispanica*, [e-journal] 35(3–4), 271–277. Available at: <http://www.iaea.org/programmes/.nafa/d1/crp/Bujan.pdf.> [Accessed 18 August 2021]

Carnevale C., Finzi G., Pisoni E., Volta M., 2009. Neuro-fuzzy and neural network systems for air quality control. *Atmospheric Environment*, [e-journal] 43(31), pp. 4811-4821. https://doi.org/10.1016/j.atmosenv.2008.07.064

Castelli, M., Clemente, F.M., Popovič, A., Silva, S., and Vanneschi, L., 2020. A Machine Learning Approach to Predict Air Quality in California. *Complexity*, [e-journal] 2020, pp.1–23. http://dx.doi.org/10.1155/2020/8049504.

Castelló Ferrer, E. et al., 2018. Personal Food Computer: A New Device for Controlled-Environment Agriculture. *Proceedings of the Future Technologies Conference (FTC)*, [e-journal] 2018, pp.1077–1096. http://dx.doi.org/10.1007/978-3-030-02683-7_79.

Charania, I. and Li, X., 2020. Smart farming: Agriculture's shift from a labor intensive to technology native industry. *Internet of Things*, [e-journal] 9, p.100142. http://dx.doi.org/10.1016/j.iot.2019.100142.

Chatterjee, S. et al., 2017. Water quality prediction: Multi objective genetic algorithm coupled artificial neural network based approach. *2017 IEEE 15th International Conference on Industrial Informatics (INDIN)*. [e-journal] http://dx.doi.org/10.1109/INDIN.2017.8104902.

Chen X., Wu J. L., and Wang L., 2005. Prediction of climate change impacts on streamflow of lake bosten using artificial neural network model (in Chinese). Journal of Lake Sciences, [e-journal] 17(3). pp. 207–212. http://dx.doi.org/10.18307/2005.0303

Choi, J. et al., 2021. Automated noise exposure assessment model for the health of construction workers. *Automation in Construction*, [e-journal] 126, p.103657. http://dx.doi.org/10.1016/j.autcon.2021.103657.

Chowdhury, M. and Sadek, A.W., 2012. Advantages and limitations of artificial intelligence. *Artificial Intelligence Applications to Critical Transportation Issues*, [e-journal] 6. Available at: < https://www.researchgate.net/publication/307928959_Advantages_and_Limitations_of_Artificial_Intelligence > [Accessed 12 August 2021].

Cibin, R., Athira, P., Sudheer, K.P. Chaubey, I., 2014. Application of distributed hydrological models for predictions in ungauged basins: a method to quantify predictive uncertainty. *Hydrological Processes*, [e-journal] 28(4), pp. 2033-2045. https://doi.org/10.1002/hyp.9721

Cleophas, T.J. and Cleophas, T.F., 2010. Artificial intelligence for diagnostic purposes: principles, procedures and limitations. *Clinical Chemistry and Laboratory Medicine*, [e-journal] 48(2). http://dx.doi.org/10.1515/CCLM.2010.045.

Codur, M. A., Atalay, A., and Unal, A., 2017. Performance evaluation of the ann and anfis models in urban traffic noise prediction. *Fresenius Environmental Bulletin,* [e-journal] 26(6/2017). pp. 4254-4260. Available at: < https://www.researchgate.net/publication/318876791_PERFORMANCE_EVALUATION_OF_THE_ANN_AND_ANFIS_MODELS_IN_URBAN_TRAFFIC_NOISE_PREDICTION> [Accessed 17 August 2021]

Cognilytica, 2021. *Worldwide AI laws and regulations 2021.* [online] Available at: < https://www.cognilytica.com/document/worldwide-ai-laws-and-regulations-2021/> [Accessed 11 April 2022].

Cortes, U., Sanchez-marre, M., Ceccaroni, L., R-Roda, I. and Poch, M., 2000. Artificial intelligence and environmental decision support systems, *Applied Intelligence*, [e-journal] 13(1), pp.77-91. http://dx.doi.org/10.1023/A:1008331413864

Corvalán, J.G., 2018. Digital and Intelligent Public Administration: transformations in the era of artificial intelligence. *A&C - Revista de Direito Administrativo & Constitucional*. [online] Available at: <https://www.researchgate.net/publication/327146580_Digital_and_Intelligent_Public_Administration_transformations_in_the_era_of_artificial_intelligence> [Accessed 15 April 2022].

Cowls, J., King, T., Taddeo, M. and Floridi, L., 2019. Designing AI for Social Good: Seven Essential Factors. SSRN Electronic Journal. [e-journal] http://dx.doi.org/10.2139/ssrn.3388669.

Creswell, J. W., 2008. *Educational research: Planning, conducting, and evaluating quantitative and qualitative research.* 3rd ed. Upper Saddle River, NJ: Pearson Education, Inc.

Cunningham, W. P. and Cunningham, M. A., 2010. *Principles of environmental science: Inquiry & applications*. 6th ed. New York: McGraw-Hill.

Davis, M. L. and Cornwell, D. A., 2008. *Introduction to Environmental Engineering*. 4th ed. New York: McGraw-Hill.

Davis, M. L. and Masten, S. J., 2013. *Principles of environmental engineering & science*. 3rd ed. New York: McGraw-Hill Professional.

Del Marmol, T., Feys B., and Probert C., 2015. *PESTLE Analysis: Understand and plan for your business environment*. [e-book] 50Minutes.com. Available at : < https://books.google.com.my/books?id=h_uQCgAAQBAJ> [Accessed 22 August 2021].

Delua, J., 2021. *Supervised vs. Unsupervised Learning: What's the Difference?.* [online] Available at: < https://www.ibm.com/cloud/blog/supervised-vs-unsupervised-learning> [Accessed 13 August 2021].

Denning, D., 2019. Is Quantum Computing a Cybersecurity Threat? American Scientist, [e-journal] 107(2), p.83. http://dx.doi.org/10.1511/2019.107.2.83.

di Pierro, F., Khu, S.-T. and Savić, D., 2006. From single-objective to multiple-objective multiple-rainfall events automatic calibration of urban storm water runoff models using genetic algorithms. *Water Science and Technology*, [e-journal] 54(6–7), pp.57–64. http://dx.doi.org/10.2166/wst.2006.609.

DIN & DKE., 2018. *German standardization roadmap industrie 4.0 Version 4.* [e-book] Berlin: DIN e. V. Available at: <https://www.din.de/blob/65354/57218767bd6da1927b181b9f2a0d5b39/roadmap-i4-0-e-data.pdf.>

Djeddou, M., Hameed, I.A. and Mokhtari, E., 2019. Soil Erosion Rate Prediction using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Geographic Information System (GIS) of Wadi Sahel-Soummam Watershed (Algeria). *2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*. [e-journal] 2019. pp. 1-7, http://dx.doi.org/10.1109/FUZZ-IEEE.2019.8858857

Doran, P.T., Zimmerman, M.K., 2009. Examining the scientific consensus on climate change, *EOS* [e-journal] 90(3), pp.20–22. https://doi.org/10.1029/2009EO030002

Dutton, T., 2018. *AI Policy 101: An Introduction to the 10 Key Aspects of AI Policy*. [online] Available at: <https://medium.com/politics-ai/ai-policy-101-what-you-need-to-know-about-ai-policy-163a2bd68d65> [Accessed 11 April 2022].

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P.V., Janssen, M., Jones, P., Kar, A.K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Medaglia, R., Le Meunier-FitzHugh, K., Le Meunier-FitzHugh, L.C., Misra, S., Mogaji, E., Sharma, S.K., Singh, J.B., Raghavan, V., Raman, R., Rana, N.P., Samothrakis, S., Spencer, J., Tamilmani, K., Tubadji, A., Walton, P. and Williams, M.D., 2019. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*. [e-journal] 57. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

ECMS, 2020. *Using PESTLE Analysis To Develop New Products In The Manufacturing Industry.* [online] Available at: <https://www.theecms.co.uk/using-pestle-analysis-to-develop-new-products-in-the-manufacturing-industry/> [Accessed 22 August 2021].

Edwards, S.D., 2018. The HeartMath coherence model: implications and challenges for artificial intelligence and robotics. AI & SOCIETY, 34(4), pp.899–905. Available at: http://dx.doi.org/10.1007/s00146-018-0834-8.

Emami, M. R., 1997. *Systematic methodology of fuzzy-logic modeling and control and application to robotics*. PhD. University of Toronto. Available at: <https://tspace.library.utoronto.ca/bitstream/1807/11727/1/NQ28276.pdf> [Accessed 14 August 2021].

European Commission (EC), 2021. *Proposal for a regulation of the European parliament and of the council laying down harmonised rules on Artifcial Intelligence (Artifcial Intelligence Act) and amending certain Union Legislative Acts.* [online] Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1623335154975&uri=CELEX%3A52021PC0206 [Accessed 11 April 2022].

Freeman, J. 2021. *PEST Chart and SWOT Analysis.* [online] Available at: < https://www.edrawsoft.com/pest-chart-swot-analysis.html> [Accessed 17 April 2022]

Fritsch, S., Guenther, F., & Guenther, M. F., 2019. Package 'neuralnet'. *Training of Neural Networks*. [online] Available at: < https://www.vps.fmvz.usp.br/CRAN/web/packages/neuralnet/neuralnet.pdf> [Accessed 9 March 2022].

Fu, L., 2018. Four Key Barriers to the Widespread Adoption of AI. [online] Available at: <https://professional.mit.edu/news/articles/four-key-barrierswidespread-adoption-ai> [Accessed 11 March 2022].

Garbade, M. J., 2018. *Regression Versus Classification Machine Learning: What's the Difference*. [online] Available at: <https://medium.com/quick-code/regression-versus-classification-machine-learning-whats-the-difference-345c56dd15f7#:~:text=Regression%20and%20classification%20are%20categorized,umbrella%20of%20supervised%20machine%20learning.&text=The%20main%20difference%20between%20them,is%20categorical%20(or%20discrete).> [Accessed 14 August 2021].

Golbaz, S., Nabizadeh, R. and Sajadi, H.S., 2019. Comparative study of predicting hospital solid waste generation using multiple linear regression and artificial intelligence. *Journal of Environmental Health Science and*

Engineering, [e-journal] 17(1), pp.41–51. http://dx.doi.org/10.1007/s40201-018-00324-z.

Goldfarb, A. and Trefler, D., 2017. AI and Trade. *Economics of AI*. [online] Available at: <https://www.nber.org/system/files/working_papers/w24254/w24254.pdf> [Accessed 12 August 2021].

Goodfellow, I., Bengio, Y. and Courville, A., 2016. *Deep learning*. [e-book] MIT press. Available at: Google Books <https://books.google.com.my/books?id=Np9SDQAAQBAJ&printsec=frontcover&dq=Deep+learning&hl=en&sa=X&ved=2ahUKEwj02O-kk9_vAhXzwTgGHa0NDnIQ6AEwAHoECAMQAg#v=onepage&q=Deep%20learning&f=false> [Accessed 13 August 2021].

Google, 2021. *Applying AI to some of the world's biggest challenges*. [online] Available at: < https://ai.google/social-good/ > [Accessed 11 April 2022].

Gürel, E. and Tat, M., 2017. SWOT analysis: a theoretical review. *Journal of International Social Research*, [e-journal] 10(51), pp.994 - 1006. http://dx.doi.org/10.17719/jisr.2017.1832.

Hadjimichael, A., Comas, J., & Corominas, L. 2016. Do machine learning methods used in data mining enhance the potential of decision support systems? A review for the urban water sector. *AI Communications*. [e-journal] 29(6), pp. 747-756. https://doi.org/10.3233/aic-160714

Hamed M. M., Khalafallah M. G., Hassanien E. A., 2004. Prediction of wastewater treatment plant performance using artificial neural networks. *Environmental Modelling and Software*, [e-journal] 19, pp. 919-928. https://doi.org/10.1016/j.envsoft.2003.10.005

Hao, K., 2019. *Training a single AI model can emit as much carbon as five cars in their lifetimes*, MIT Technology Review, [online] Available at: <https://www.technologyreview.com/2019/06/06/239031/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/> [Accessed 12 August 2021].

Hao, K., 2019. *Why AI is a threat to democracy—and what we can do to stop it*, MIT Technology Review. [online] Available at: <https://www.technologyreview.com/2019/02/26/66043/why-ai-is-a-threat-to-democracyand-what-we-can-do-to-stop-it/> [Accessed 15 April 2022].

Hong, J., Kang, H., Hong, T., Park, H.S. and Lee, D.E., 2021. Development of a prediction model for the proportion of buildings exposed to construction noise in excess of the construction noise regulation at urban construction sites. *Automation in Construction*, [e-journal] 125(March), p.103656. https://doi.org/10.1016/j.autcon.2021.103656.

Hong, T., Ji, C., Park, J., Leigh, S.-B. and Seo, D., 2015. Prediction of

Environmental Costs of Construction Noise and Vibration at the Preconstruction Phase. *Journal of Management in Engineering*, [e-journal] 31(5), p.04014079.

Hvidtfeldt, U.A. et al., 2018. Evaluation of the Danish AirGIS air pollution modeling system against measured concentrations of PM2.5, PM10, and black carbon. *Environmental Epidemiology*, [e-journal] 2(2), p.e014. http://dx.doi.org/10.1097/EE9.0000000000000014.

IBM Cloud Education, 2020a. *What is Artificial Intelligence (AI)?*. [online] Available at: < https://www.ibm.com/cloud/learn/what-is-artificial-intelligence > [Accessed 12 August 2021].

IBM Cloud Education, 2020b. *What is supervised learning?*. [online] Available at: <https://www.ibm.com/cloud/learn/supervised-learning#toc-how-superv-A-QjXQz-> [Accessed 13 August 2021].

IBM Cloud Education, 2020c. *What are neural networks?*. [online] Available at: <https://www.ibm.com/my-en/cloud/learn/neural-networks#toc-types-of-n-YgdI1-Kt> [Accessed 13 August 2021].

IBM Cloud Education, 2020d. *Ai vs. Machine learning vs. Deep learning vs. Neural networks: what's the difference?*. [online] Available at: < https://www.ibm.com/cloud/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks> [Accessed 13 August 2021].

IBM Cloud Education, 2020e. *What are Convolutional Neural Networks?*. [online] Available at: < https://www.ibm.com/cloud/learn/convolutional-neural-networks#toc-how-do-con--z4UwR2M> [Accessed 13 August 2020].

IBM Cloud Education, 2020f. *What are Recurrent Neural Networks?*. [online] Available at: <https://www.ibm.com/cloud/learn/recurrent-neural-networks#toc-what-are-r-btVB33l5> [Accessed 13 August 2022].

Jahandideh S., Jahandideh S., Asadabadi E. B., Askarian M., Movahedi M., Mehdi M., Hosseini S., Jahandideh M., 2009. The use of artificial neural networks and multiple linear regression to predict rate of medical waste generation. *Waste Management*, 29, pp. 2874-2879. https://doi.org/10.1016/j.wasman.2009.06.027

Jang J. S. R., 1993.ANFIS - Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems Man and Cybernetics,* [e-journal] 23(3), pp. 665-685. http://dx.doi.org/10.1109/21.256541

Jantzen J., 1998. *Design of fuzzy controllers*. Technical Report (No: 98-E864) Technical University of Denmark. Available at: < https://www.researchgate.net/publication/228751652_Design_of_Fuzzy_Controllers > [Accessed 14 August 2021].

Jonsson, A., and Svensson, V., 2016. *Systematic lead time analysis*. Master. Chalmers University of Technology. Available at: <https://publications.lib.chalmers.se/records/fulltext/238746/238746.pdf> [Accessed 16 March 2022].

Kahn, K. and Winters, N., 2017. Child-Friendly Programming Interfaces to AI Cloud Services. *Data Driven Approaches in Digital Education*, [e-journal] pp.566–570. http://dx.doi.org/10.1007/978-3-319-66610-5_64.

Kartik, Rahul, Gaurav, Rishabh, and Chawla, P., 2020. Implementation of Air Quality Index using Machine Learning Techniques. *International Research Journal of Engineering and Technology*, [e-journal] 7(5), pp. 6738-6744 Available at: < www.irjet.net > [Accessed 16 August 2021].

Karul C., Soyupak S., Cilesiz A. F., Akbay N., Germen E., 2000. Case studies on the use of neural networks in eutrophication modelling. *Ecological Modelling*, [e-journal] 134(2-3), pp. 145-152. http://dx.doi.org/10.1016/S0304-3800(00)00360-4

Kasprzyk, J.R., Nataraj, S., Reed, P.M., Lempert, R.J., 2013. Many objective robust decision making for complex environmental systems undergoing change. *Environ. Model. Softw.* [e-journal] 42(2013), 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Kasprzyk, Joseph R., Reed, Patrick M., Hadka, David M., 2016. Battling arrow's paradox to discover robust water management alternatives. *Journal of Water Resources Planning and Management*. [e-journal] 142(2), p.04015053. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000572

Ke, Q., Liu, J., Bennamoun, M., An, S., Sohel, F. and Boussaid, F., 2018. Computer vision for human–machine interaction. In *Computer Vision for Assistive Healthcare*, [e-journal] pp.127 - 145. https://doi.org/10.1016/B978-0-12-813445-0.00005-8.

Kerravala, Z., 2018. *Want to use AI and machines learning? You need the right infrastructure*. [online] Available at: <https://www.networkworld.com/article/3329861/want-to-use-ai-and-machine-learning-you-need-the-right-infrastructure.html> [Accessed 11 April 2022].

Khairjadaan and Okasha, A., 2015. Tp. 1: Developing a traffic noise prediction model using artificial neural network (ANN). [online]. Available at: <https://www.researchgate.net/publication/348311266_DEVELOPING_A_TRAFFIC_NOISE_PREDICTION_MODEL_USING_ARTIFICIAL_NEURAL_NETWORK_ANN> [Accessed 17 August 2021].

Kim, K.-S. and Park, J.-H., 2009. A Survey of Applications of Artificial Intelligence Algorithms in Eco-environmental Modelling, *Environmental Engineering Research*, [e-journal] 14(2), pp.102–110. http://dx.doi.org/10.4491/eer.2009.14.2.102

Konar, A., 2018. *Artificial intelligence and soft computing: behavioral and cognitive modelling of the human brain.* [e-book] Boca Raton, Florida: CRC Press. Available at: Google Books <https://books.google.com.my/books?id=qn50DwAAQBAJ&printsec=frontcover&dq=Artificial+intelligence+and+soft+computing:+behavioral+and+cognitive+modelling+of+the+human+brain.&hl=en&sa=X&ved=2ahUKEwik_YK8lt_vAhWVyzgGHQLhBCwQ6AEwAHoECAMQAg#v=onepage&q=Artificial%20intelligence%20and%20soft%20computing%3A%20behavioral%20and%20cognitive%20modelling%20of%20the%20human%20brain.&f=false> [Accessed 26 June 2021]

Kothari, C.R., 2004. *Research methodology: Methods and techniques. New Age International*. [e-book] New Age Publications. Available at: Google Books <https://books.google.com.my/books?id=hZ9wSHysQDYC&printsec=frontcover&dq=Research+methodology:+Methods+and+techniques.+New+Age+International.&hl=en&sa=X&ved=2ahUKEwiczK6Vl9_vAhVbwzgGHUguBPsQ6AEwAHoECAIQAg#v=onepage&q=Research%20methodology%3A%20Methods%20and%20techniques.%20New%20Age%20International.&f=false> [Accessed 22 August 2021].

Kumar Tiwari, M., Bajpai, S. and Dewangan, U.K., 2012. Prediction of industrial solid waste with ANFIS Model and its comparison with ANN Model-A case study of Durg-Bhilai Twin City India. *International journal of engineering and innovative technology*, [online] 2(6), pp.192–201. Available at: <https://www.researchgate.net/publication/275646314_Prediction_of_Industrial_Solid_Waste_with_ANFIS_Model_and_its_comparison_with_ANN_Model-A_Case_Study_of_Durg-Bhilai_Twin_City_India> [Accessed 15 August 2021].

Kusan H., Aytekin O., and Ozdemir I., 2010. The use of fuzzy logic in predicting house selling price. *Expert System with Applications*, [e-journal] 37(3), pp. 1808-1813. http://dx.doi.org/10.1016/j.eswa.2009.07.031

Kyeremanteng, P., 2020. *Artificial Intelligence and Environment the Pros and Cons*, [online] Available at: <https://www.modernghana.com/news/1050730/artificial-intelligence-and-environment-the-pros.html> [Accessed 12 August 2021].

Le, Viet T., Nguyen H. Quan, Ho H. Loc, Nguyen T. Thanh Duyen, Tran D. Dung, Hiep D. Nguyen, and Quang H. Do. 2019. A Multidisciplinary Approach for Evaluating Spatial and Temporal Variations in Water Quality. *Water*. [e-journal] 11(4), pp. 853. https://doi.org/10.3390/w11040853

LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. *Nature*, [e-journal] 521(7553), pp.436 - 444. https://doi.org/10.1038/nature14539

Li, B., Yang, G., Wan, R., Dai, X. & Zhang, Y., 2016. Comparison of random forests and other statistical methods for the prediction of lake water level: a case study of the Poyang Lake in China. *Hydrology Research*, in press.

Li, V.O.K., Lam, J.C.K. and Cui, J., 2021. AI for Social Good: AI and Big Data Approaches for Environmental Decision-Making. *Environmental Science & Policy*, [e-journal] 125, pp.241–246. Available at: http://dx.doi.org/10.1016/j.envsci.2021.09.001.

Liakos, K. et al., 2018. Machine Learning in Agriculture: A Review. *Sensors*, [e-journal] 18(8), p.2674. http://dx.doi.org/10.3390/s18082674.

Lim, M.H., 2017. *Continuous Noise Mapping Prediction Techiniques Using the Stochastic Modelling*. [online] Available at: < https://www.semanticscholar.org/paper/Continuous-noise-mapping-predication-techniques-the-Lim/3dd9b6badf9ee2f4e477c8a2938ee81a5f9f4788 > [Accessed 15 April 2022]

Liu, R., Rong, Y., and Peng, Z., 2020. A review od medical artificial intelligence. *Global Health Journal*, [e-journal] 4(2), pp.42-45. https://doi.org/10.1016/j.glohj.2020.04.002

Liu, Z. et al., 2010. Application of artificial neural networks in global climate change and ecological research: An overview. *Chinese Science Bulletin*, [e-journal] 55(34), pp.3853–3863. http://dx.doi.org/10.1007/s11434-010-4183-3.

Lucci, S. and Kopec, D., 2016. *Artificial intelligence in the 21st century: a living introduction.* 2nd ed. [e-book] Dulles, VA: David Pallai. Available at: Google Books <https://books.google.com.my/books?id=wje_DgAAQBAJ&pg=PT8&source=gbs_selected_pages&cad=3#v=onepage&q&f=false> [Accessed 26 June 2021]

Luo, H., Xiong, C., Fang, W., Love, P.E., Zhang, B. and Ouyang, X., 2018. Convolutional neural networks: Computer vision-based workforce activity assessment in construction. *Automation in Construction*, [e-journal] 94, pp.282 - 289. https://doi.org/10.1016/j.autcon.2018.06.007.

Madsen, D.Ø., 2016. SWOT Analysis: A Management Fashion Perspective. *International Journal of Business Research*, 16(1), pp.39–56.

Maher, K., 2020. *Environmental Intelligence: Applications of AI to Climate Change, Sustainability, and Environmental Health*. [online] Stanford HAI. Available at: <https://hai.stanford.edu/news/environmental-intelligence-applications-ai-climate-change-sustainability-and-environmental> [Accessed 27 June 2021].

Makridakis, S., 2018. Forecasting the impact of artificial intelligence, Part 3 of 4: The potential effects of AI on businesses, manufacturing, and commerce. *Foresight: The International Journal of Applied Forecasting*, [e-journal] (49), p. 18–27. Available at: < https://ideas.repec.org/a/for/ijafaa/y2018i49p18-27.html> [Accessed 16 March 2022].

Mann M. E., 2009. Do global warming and climate change represent a serious threat to our welfare and environment. *Social Philosophy and Policy Foundation*, [e-journal] 26(20), pp 193–230. https://doi.org/10.1017/S0265052509090220

Mansourkhaki, A., Berangi, M., Haghiri, M. and Haghani, M., 2018. A neural network noise prediction model for tehran urban roads. *Journal of Environmental Engineering and Landscape Management*, [e-journal] 26(2), pp.88–97. http://dx.doi.org/10.3846/16486897.2017.1356327.

Masood, A. and Ahmad, K., 2021. A review on emerging artificial intelligence (AI) techniques for air pollution forecasting: Fundamentals, application and performance. *Journal of Cleaner Production*, [e-journal] 322, p.129072. http://dx.doi.org/10.1016/j.jclepro.2021.129072.

McCarthy, J, 2004. What is artificial intelligence?. *Computer Science Department,* [online] Available at: <http://www-formal.stanford.edu/jmc/> [Accessed 12 August 2021]

Mijwel, M.M., 2018. Artificial Neural Networks Advantages and Disadvantages. [online] Available at: < https://www.linkedin.com/pulse/artificial-neural-networks-advantagesdisadvantages-maad-m-mijwel > [Accessed 11 March 2022].

Mitchell, M., 2019. Artificial Intelligence Hits the Barrier of Meaning. *Information*, [e-journal] 10(2), p.51. http://dx.doi.org/10.3390/info10020051.

Mitchell, R.S., Michalski, J.G. and Carbonell, T.M., 2013. *An artificial intelligence approach*. [e-book] Berlin: Springer. Available at: Google Books <https://books.google.com.my/books?id=-eqpCAAAQBAJ&printsec=frontcover&dq=An+artificial+intelligence+approach.&hl=en&sa=X&ved=2ahUKEwiixLzemd_vAhVNxTgGHeocBREQ6AEwBHoECAYQAg#v=onepage&q=An%20artificial%20intelligence%20approach.&f=false> [Accessed 12 August 2021].

Modgil, S. and Prakken, H., 2013. A general account of argumentation with preferences. *Artificial Intelligence*, [e-journal] *195*, pp.361 - 397. https://doi.org/10.1016/j.artint.2012.10.008.

Moisen, G.G. and Frescino, T.S., 2002. Comparing five modelling techniques for predicting forest characteristics. *Ecological Modelling*, [e-journal] 157(2–3), pp.209–225. http://dx.doi.org/10.1016/S0304-3800(02)00197-7.

Monti, L., Berang, M., Haghiri, M. and Haghani, M., 2020. RaveGuard: A Noise Monitoring Platform Using Low-End Microphones and Machine Learning. *Sensors*, [e-journal] 20(19), p.5583. http://dx.doi.org/10.3390/s20195583.

MSV, J., 2018. *Three Factors That Accelerate The Rise of Artificial Intelligence*. [online] Available at: <https://www.forbes.com/sites/janakirammsv/2018/05/27/here-are-three-

factors-that-accelerate-the-rise-of-artificial-intelligence/?sh=7d9c2f21add9> [Accessed 11 March 2022].

Mulhern, O., 2021. *Can AI Help Achieve Environmental Sustainability?* [online]. Available at: <https://earth.org/data_visualization/ai-can-it-help-achieve-environmental-sustainable/> [Accessed 9 March 2022].

Mullan, E., 2018. 5 Current Limitations of Artificial Intelligence to Marketers. Hurree, [blog] 20 December. Available at: < https://blog.hurree.co/blog/limitations-of-artificial-intelligence-mobile-marketing > [Accessed 11 March 2022].

Nadimpalli, M., 2017. Artificial intelligence risks and benefits. *International Journal of Innovative Research in Science, Engineering and Technology,* [online] 6(6). Available at : < https://www.researchgate.net/profile/Meenakshi-Nadimpalli/publication/319321806_Artificial_Intelligence_Risks_and_Benefits/links/59a47dd20f7e9b4f7df37ab9/Artificial-Intelligence-Risks-and-Benefits.pdf > [Accessed 12 August 2021]

NASEM (National Academies of Sciences, Engineering, and Medicine), 2019. *Environmental Engineering for the 21st Century: Addressing Grand Challenges.* Washington, DC: The National Academies Press. [e-book] https://doi.org/10.17226/25121.

Nelson, J., 2020. *AI in Water: 10 Ways AI is Changing the Water Industry.* [online]. Available at: < https://www.innovyze.com/en-us/blog/ai-in-water-10-ways-ai-is-changing-the-water-industry > [Accessed 9 March 2022].

Neustadter, D., 2020. *Why AI Needs Security*. [online] Available at: <https://www.synopsys.com/designware-ip/technical-bulletin/why-ai-needs-security-dwtb-q318.html> [Accessed 11 April 2022].

Newquist, H.P., 1994. *The Brain Makers: Genius, Ego, And Greed in the Quest For Machines That Think*, New York: Macmillan/SAMS.

Nishant, R., Kennedy, M. and Corbett, J., 2020. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management, [e-journal] 53, p.102104. http://dx.doi.org/10.1016/j.ijinfomgt.2020.102104.

Noori R., Hoshyaripour G., Ashrafi K., Araabi B. N., 2010. Uncertainty analysis of developed ANN and ANFIS models in prediction of carbon monoxide daily concentration. *Atmospheric Environment*, [e-journal] 44(4), pp. 476-482. https://doi.org/10.1016/j.atmosenv.2009.11.005

Ohmae, K., 2006. The mind of a strategist. *Management Today*, [e-journal] 22(1).

Olyaie, E., Zare Abyaneh, H., & Danandeh Mehr, A., 2017. A comparative analysis among computational intelligence techniques for dissolved oxygen prediction in Delaware River. *Geoscience Frontier,* [e-journal] 8(3), pp. 517-527. https://doi.org/10.1016/j.gsf.2016.04.007

Onkal-Engin G., Demir I., Engin S. N., 2005. Determination of the relationship between sewage odour and BOD by neural networks. *Environmental Modelling and Software,* [e-journal] 20(7), pp. 843-850. https://doi.org/10.1016/j.envsoft.2004.04.012

Osiński, B. and Budek, K., 2018. *What is reinforcement learning? The complete guide*. [online] Available at: < https://deepsense.ai/what-is-reinforcement-learning-the-complete-guide/#top > [Accessed 13 August 2021].

Ozcan F., Atis C. D., Karahan O., Uncuoglu E., Tanyildizi H., 2009. Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete. *Advanced in Engneering Soft*ware, [e-journal] 40(9), pp. 856-863. https://doi.org/10.1016/j.advengsoft.2009.01.005

Ozkaya B., Sahinkaya E., Nurmi P., Kaksonen A. H., Puhakka J. A., 2008. Biologically Fe^{2+} oxidizing fluidized bed reactor performance and controlling of Fe^{3+} recycle during heap bioleaching: an artificial neural network-based model. *Bioprocess Biosyst Eng.,* [e-journal] 31(2), pp. 111-117. https://doi.org/10.1007/s00449-007-0153-9

Palomares, I. et al., 2021. A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects. Applied Intelligence, 51(9), pp.6497–6527. Available at: http://dx.doi.org/10.1007/s10489-021-02264-y.

Peavy H.S., Rowe D.R., Tchobanoglous G., 1985. *Environmental engineer*ing. UK: McGraw-Hill.

Prexiso, n.d. *PPX-130 Phonometer*. [online] Available at: <http://www.prexiso.com/products/instruments/Environment_And_Special_Measure/PPX-130_PHONOMETER.html> [Accessed 17 August 2021].

Quillian, M.R., 1968. Semantic memory. In *semantic Information Processing*, pp.227-270.

Rani, S. and Kautish, S., 2018. Association Clustering and Time Series Based Data Mining in Continuous Data for Diabetes Prediction. In *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, [e-journal] pp.1209 - 1214. https://doi.org/10.1109/ICCONS.2018.8662909

Raphael, B., 1976. *The thinking computer*. San Francisco, CA: W.H. Freeman.

Rihani R., Bensmaili A., Legrand J., 2009. Fuzzy logic modeling tracer response in milli torus reactor under aerated and non-aerated conditions. *Chemical*

Engineering Journal, [e-journal] 152, pp. 566-574. https://doi.org/10.1016/j.cej.2009.05.025

Risse, M., 2019. Human Rights and Artificial Intelligence: An Urgently Needed Agenda. *Human Rights Quarterly*, [e-journal] 41(1), pp.1–16. http://dx.doi.org/10.1353/hrq.2019.0000.

Rory, C.J., 2014. Stephen Hawking warns artificial intelligence could end mankind. *BBC News,* [onine] 2 December. Available at: <https://www.bbc.com/news/technology-30290540> [Accessed 11 April 2022].

Russell, S.J., 2016. Should we fear supersmart robots. *Scientific American*. [e-journal] 314 (2016), pp. 58-59. https://doi.org/10.1038/scientificamerican0616-58

Sahla, N. E., 2018. *A Deep Learning Prediction Model for Object Classification*. Master of Science Thesis. Delft University of Technology. [online] Available at : < http://resolver.tudelft.nl/uuid:f7667cb4-70d4-4b82-ac1b-75df476655cd > [Accessed 13August 2021]

Saiz-Rubio, V. and Rovira-Más, F., 2019. VineScout_ROBOTdata_22July2019_TN102. [online] Available at: <https://zenodo.org/record/3451840.>

Saiz-Rubio, V. and Rovira-Más, F., 2020. From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. *Agronomy*, [e-journal] 10(2), p.207. http://dx.doi.org/10.3390/agronomy10020207.

Salami, E.S. and Ehteshami, M., 2016. Application of neural networks modeling to environmentally global climate change at San Joaquin Old River Station. *Modeling Earth Systems and Environment*, [e-journal] 2(1). http://dx.doi.org/10.1007/s40808-016-0094-x.

Šalić, A. and Zelić, B., 2018. Introduction to environmental engineering. *Physical Sciences Reviews*, [e-journal] 3(3), pp. 20160115. https://doi.org/10.1515/psr-2016-0115

Saunders, M. N., Lewis, P., Thornhill, A., & Bristow, A., 2019. *Research Methods for Business Students*. 8th ed. London, England: Pearson Education.

Schober, K., 2020. *How to increase efficiency over the entire lifecycle chain.* [online] Available at: <https://www.rolandberger.com/en/Insights/Publications/Artificial-intelligence-in-the-construction-industry.html#:~:text=AI%20based%20solutions%20can%20help,productivity%20within%20construction%20execution%20itself.> [Accessed 13 August 2021].

Setyaningrum, A.H. and Swarinata, P.M., 2014. Weather prediction application based on ANFIS (Adaptive neural fuzzy inference system) method in West Jakarta region. *2014 International Conference on Cyber and IT Service Management (CITSM)*. [e-journal] 2014, pp. 113-118, http://dx.doi.org/10.1109/CITSM.2014.7042187

Shanmuganathan, S., 2016. Artificial Neural Network Modelling: An Introduction. *Studies in Computational Intelligence*, [e-journal] pp.1–14. https://doi.org/10.1007/978-3-319-28495-8_1

Sharma, A., Vijay, R., L. Bodhe, G. and G. Malik, L., 2014. Adoptive Neuro-Fuzzy Inference System for Traffic Noise Prediction. *International Journal of Computer Applications*, [e-journal] 98(13), pp.14–19. http://dx.doi.org/10.5120/17243-7579.

Sharma, V., and Yuden, K., 2021. Imputing missing data in hydrology using machine learning models, *International journal of engineering research & technology (Ahmedabad)*, [e-journal] 10(01), pp.78 – 82. http://dx.doi.org/10.17577/IJERTV10IS010011

Silvestro, D., Goria, S., Sterner, T. and Antonelli, A., 2022. Improving biodiversity protection through artificial intelligence. *Nature Sustainability*. [e-journal] http://dx.doi.org/10.1038/s41893-022-00851-6

Song, Y., Wang, Y., Liu, F. and Zhang, Y., 2017. Development of a hybrid model to predict construction and demolition waste: China as a case study. *Waste Management*, [e-journal] 59, pp.350–361. http://dx.doi.org/10.1016/j.wasman.2016.10.009.

Soni, N., 2018. *14 Ways AI Will Benefit Or Harm Society*. [online] Available at: <https://www.forbes.com/sites/forbestechcouncil/2018/03/01/14-ways-ai-will-benefit-or-harm-society/?sh=1c90ffb44ef0> [Accessed 5 February 2021].

Srivastava A. K., Nema A. K., 2008. Forecasting of solid waste composition using fuzzy regression approach: a case of Delhi. *International Journal of Environment and Waste Management*, [e-journal] 2(1-2), pp. 65-74. https://doi.org/10.1504/IJEWM.2008.016992

Sun, T.Q. and Medaglia, R., 2019. Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, [e-journal] 36(2), pp.368–383. http://dx.doi.org/10.1016/j.giq.2018.09.008.

Suparta, W. and Samah, A.A., 2020. Rainfall prediction by using ANFIS times series technique in South Tangerang, *Indonesia. Geodesy and Geodynamics*, [e-journal] 11(6), pp.411–417. http://dx.doi.org/10.1016/j.geog.2020.08.001.

Szczepanski, M., 2019. Economic impacts of artificial intelligence (AI). Available at: <

https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/637967/EPRS_BRI(2019)637967_EN.pdf>

Tehrani, A. and Karbasi, H., 2017. A novel integration of hyper-spectral imaging and neural networks to process waste electrical and electronic plastics. *2017 IEEE Conference on Technologies for Sustainability (SusTech)*. [e-journal] 2017, pp. 1-5. https://doi.org/10.1109/SusTech.2017.8333533

Tizhoosh, H. and Pantanowitz, L., 2018. Artificial intelligence and digital pathology: Challenges and opportunities. *Journal of Pathology Informatics*, [e-journal] 9(1), p.38. http://dx.doi.org/10.4103/jpi.jpi_53_18.

Tu, J.V., 1996. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. Journal of Clinical Epidemiology, [e-journal] 49(11), pp.1225-1231. https://doi.org/10.1016/S0895-4356(96)00002-9.

Turing, A.M., 1950. Computing machinery and intelligence. *Mind,* [e-journal] 49, pp. 433-460. Available at: <https://www.csee.umbc.edu/courses/471/papers/turing.pdf> [Accessed 12 August 2021].

Van de Poel, I. 2018. Design for value change. *Ethics and Information Technology*. [e-journal] 23(1), pp. 27–31. https://doi.org/10.1007/s10676-018-9461-9

Van Thienen, P. 2019. *Responsible AI for the water sector?*. KWRwater [blog] 10 October. Available at: https://www.kwrwater.nl/en/actueel/responsible-ai-for-the-water-sector/ [Accessed 11 March 2022].

Van Thienen, P., Alphen, H., Stichting Toegepast Onderzoek Waterbeheer, Brunner, A., Fujita, Y., Hillebrand, B., Sjerps, R., Summeren, J., Verschoor, A., Wullings, B., 2018. *Explorations in Data Mining for the Water Sector*. [e-book] Nieuwegein, The Netherlands: KWR Watercycle Research Institute. Available at: Google Books < https://books.google.com.my/books/about/Explorations_in_Data_Mining_for_the_Wate.html?id=VrV1zQEACAAJ&redir_esc=y> [Accessed 11 March 2022].

Vinuesa, R. et al., 2020. The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, [e-journal] 11(1). http://dx.doi.org/10.1038/s41467-019-14108-y.

Wang, L. and Wang, X.V., 2016. Outlook of Cloud, CPS and IoT in Manufacturing. *Cloud-Based Cyber-Physical Systems in Manufacturing,* [e-journal] pp.377–398. http://dx.doi.org/10.1007/978-3-319-67693-7_15.

Wang, L., Törngren, M. and Onori, M., 2015. Current status and advancement of cyber-physical systems in manufacturing. *Journal of Manufacturing Systems*, [e-journal] 37, pp.517–527. Available at: http://dx.doi.org/10.1016/j.jmsy.2015.04.008.

Wang, X., Li, X. and Leung, V.C.M., 2015. Artificial Intelligence-Based Techniques for Emerging Heterogeneous Network: State of the Arts, Opportunities, and Challenges. *IEEE Access*, [e-journal] 3, pp.1379–1391. http://dx.doi.org/10.1109/ACCESS.2015.2467174.

Waseem, M., Ajmal, M., & Kim, T.W., 2015. Ensemble hydrological prediction of streamflow percentile at ungauged basins in Pakistan. *Journal of Hydrology*, [e-journal] 525, pp. 130-137. https://doi.org/10.1016/j.jhydrol.2015.03.042

Wieland D., Wotawa F., Wotawa G., 2002. From neural networks to qualitative models in environmental engineering. *Computer-Aided Civil and Infrastructure Engineering*, [e-journal] 17(2), pp. 104-118. http://dx.doi.org/10.1111/1467-8667.00259

Wu, J., 2019. *A.I., Machine Learning, Deep Learning Explained Simply*. [online] Available at: <https://towardsdatascience.com/ai-machine-learning-deep-learning-explained-simply-7b553da5b960> [Accessed 13 August 2021].

Xhienne, 2007. *SWOT Analysis.* Available at: <https://upload.wikimedia.org/wikipedia/commons/0/0b/SWOT_en.svg> [Accessed 22 August 2021].

Yabunaka K., Hosomi M., Murakami A., 1997. Novel application of a back-propagation artificial neural network model formulated to predict algal bloom. *Water Science and Technology,* [e-journal] 36(7), pp. 89-97. https://doi.org/10.1016/S0273-1223(97)00464-2

Yetilmezsoy K., 2006. Determination of optimum body diameter of air cyclones using a new empirical model and a neural network approach. *Environmental Engineering Sciscience*, [e-journal] 23(4), pp. 680-690. http://dx.doi.org/10.1089/ees.2006.23.680

Yetilmezsoy K., Demirel S., 2007. Artificial neural network (ANN) approach for modeling of Pb(II) adsorption from aqueous solution by Antep pistachio (Pistacia Vera L.) shells. *Journal of hazardous materials*, [e-journal] 153(3), pp. 1288-1300. https://doi.org/10.1016/j.jhazmat.2007.09.092

Yetilmezsoy K., Sapci-Zengin Z., 2009. Stochastic modeling applications for the prediction of COD removal efficiency of UASB reactors treating diluted real cotton textile wastewater. *Stochastic Environmental Research and Risk Assessment*, [e-journal] 23, pp. 13-26. https://doi.org/10.1007/s00477-007-0191-5

Yetilmezsoy, K., Fingas, M. and Fieldhouse, B., 2011. An adaptive neuro-fuzzy approach for modeling of water-in-oil emulsion formation. *Colloids and Surfaces A: Physicochemical and Engineering Aspects*, [e-journal] 389(1–3), pp.50–62. https://doi.org/10.1016/j.colsurfa.2011.08.051

Yetilmezsoy, K., Ozkaya, B. and Cakmakci, M., 2011. Artificial intelligence-based prediction models for environmental engineering, *Neural Network World*, [e-journal] 21(3), pp.193–218. http://dx.doi.org/10.14311/nnw.2011.21.012

Yildirim Y., Bayramoglu M., 2006. Adaptive neuro-fuzzy based modeling for prediction of air pollution daily levels in city of Zonguldak. *Chemosphere*, [e-journal] 63(9), pp. 1575-1582. https://doi.org/10.1016/j.chemosphere.2005.08.070

Zade J. G., Noori R., 2008. Prediction of municipal solid waste generation by use of artificial neural network: A case study of Mashhad. *International Journal of Environmental Research*, [e-journal] 2(1), pp. 13-22. Available at: < https://www.researchgate.net/publication/27794359_Prediction_of_Municipal_Solid_Waste_Generation_by_Use_of_Artificial_Neural_Network_A_Case_Study_of_Mashhad > [Accessed 16 August 2021]

Zannin, P.H.T., do Nascimento, E.O., da Paz, E.C. and do Valle, F., 2018. Application of Artificial Neural Networks for Noise Barrier Optimization. Environments, [e-journal] 5(12), p.135. Available at: http://dx.doi.org/10.3390/environments5120135

Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J., Ganguli, D., Grosz, B., Lyons, T., Manyika, J., Niebles, J.C., Sellitto, M., Shoham, Y., Clark, J. and Perrault, R., 2021. *The ai index 2021 annual report*. [online] AI Index Steering Committee, Human-Centered AI Institute, Stanford University, Stanford, CA. Available at: <https://aiindex.stanford.edu/report/> [Accessed 26 June 2021]

Zhang, Y. and Wallace, B., 2015. A sensitivity analysis of (and practitioners' guide to) convolutional neural networks for sentence classification. *arXiv [cs.CL]*. Available at: < https://arxiv.org/abs/1510.03820v4 > [Accessed 14 August 2021]

Zhang, Z., 2016. A gentle introduction to artificial neural networks. *Annals of Translational Medicine*, [e-journal] 4(19), p.370. 10.21037/atm.2016.06.20.

Zhao, L., Dai, T., Qiao, Z., Sun, P., Hao, J., Yang, Y., 2019. Application of artificial intelligence to wastewater treatment: Abibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Safety and Environmental Protection.* [e-journal] 133, pp. 169-182. https://doi.org/10.1016/j.psep.2019.11.014.

Zhao, Z., Meng, F.-R., Yang, Q. and Zhu, H., 2018. Using Artificial Neural Networks to Produce High-Resolution Soil Property Maps. *Advanced Applications for Artificial Neural Networks*. InTech. https://doi.org/10.5772/intechopen.70705

Zhu, Z., Chen, B., Zhao, Y. and Ji, Y., 2021. Multi-sensing paradigm based urban air quality monitoring and hazardous gas source analyzing: a review. *Journal of Safety Science and Resilience*, [e-journal] 2(3), pp.131–145. http://dx.doi.org/10.1016/j.jnlssr.2021.08.004.

Zwolsman J.J.G, Van Bokhoven A.J., 2007. Impact of summer droughts on water quality of the Rhine River—a preview of climate change?. *Water Sci Technol.* [e-journal] 56(4), pp. 45-55. https://doi.org/10.2166/wst.2007.535.