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Thème

Modeling of Geothermal EAHE Outputs Using Convolutional Neural Network and Artificial Neural Network in Ghardaia

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Thanks

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Dedicates

I would like to dedicate this modest work:

To my dear parents **BOUAMER Ali** *&* **METMATE Mounira** *for their support, understanding and great tenderness. To* **my twin sister Zineb** *who always supported me during all my life and studying years*

To my best friends **BERRIGHAID Fatima Zahra** *&* **DEDDOUCH Chaima**.

Moreover, to all detainees of opinion all around the world

chaima

Abstract

Artificial Intelligence (AI) and thermal energy systems are two distinct fields and the role of both in advancing scientific research and supporting sustainable development, making this study saturated with knowledge diversity, where deep learning was exploited to optimise the performance of geothermal heat exchangers. A feed-forward back-propagation network and a convolutional neural network were used to use the data obtained in a specific period to build an accurate predictive model that helps optimise the system performance.

Keywords: Earth-Air Heat Exchanger (EAHE), Geothermal Energy, Convolutional Neural Network (CNN),and Artificial Neural Network (ANN) , Deep Learning, Heat Transfer.

ملخص

تعتبر أنظمة الذكاء الاصطناعي وأنظمة الطاقة الحرارية مجالان منفصلان عن بعضهما البعض ويبرز دور كليهما في تطوير البحث العلمي ودعم التنمية المستدامة، مما يجعل هذه الدراسة مشبعة بالتنوع المعرفي، حيث تم استغلال التعلم العميق في تحسين أداء المبادلات الحرارية الهوائية الأرضية. وقد تم الإعتماد على شبكة التغذية الأمامية الخلفية والتغذية الخلفية الأمامية و شبكة العصبية التلافقية و باستخدام البيانات التي تم الحصول عليها في فترة محددة لبناء نموذج تنبؤي دقيق يساعد على تحسين أداء النظام.

الكلمات المفتاحية: مبادل حراري أرضي-هوائي ((EAHE، الطاقة الحرارية الأرضية، الشبكة العصبية التلافيفية ((CNN، والشبكة العصبية الاصطناعية ((ANN، التعلم العميق، نقل الحرارة.

Résumé

L'intelligence artificielle (IA) et les systèmes d'énergie thermique sont deux domaines distincts et le rôle des deux dans l'avancement de la recherche scientifique et le soutien au développement durable, ce qui rend cette étude saturée de connaissances diverses, où l'apprentissage profond a été exploité pour optimiser la performance des échangeurs de chaleur géothermiques. Un réseau de rétro-propagation feed-forward et un réseau neuronal convolutif ont été utilisés pour utiliser les données obtenues au cours d'une période spécifique afin de construire un modèle prédictif précis qui permet d'optimiser les performances du système.

Mots clés : Échangeur de chaleur terre-air (EAHE), énergie géothermique, réseau neuronal convolutif (CNN), réseau neuronal artificiel (ANN), apprentissage profond, transfert de chaleur.

List of figures:

Chapter I

Chapter II

Chapter III

List of tables:

Symbols

Nomenclature	
T	Temperature (K)
$T_{\mathbf{out}}$	Outlet air temperature (K)
T_{inl}	Inlet air temperature (K)
α	the soil thermal diffusivity in $m^2\ S^{-1}$
z	the depth below ground surface
λ_{siol}	the soil thermal conductivity $Wm^{-1}°C^{-1}$
C_{siol}	the soil specific heat $J\ kg^{-1}°C^{-1}$
ρ	the soil density kg m^{-1}
λ_{pipe}	the $pipe$ thermal conductivity$Wm^{-1}°C^{-1}$
r_e	pipe radius(m)
r_i	radius of cylinder denoting thickness of soil surrounding pipe(m)
R_{pipe}	The thermal resistance of the pipe
∅	The heat transfer
R_{soil}	The thermal resistance of the soil
R_{conv}	The convective thermal resistance
h_{conv}	The coefficient of heat transfer
Nu	The number of Nusselt
Re	The Reynolds numbers
Pr	Prandtl numbers
D	Pipe diameter [m]
V_{air}	Average air velocity inside the pipe [m/s]
ν	Kinematic viscosity [m^2/s]
ρ	density of air [kg/m^2]
Cp	Specific heat capacity [J/(kg·K)]

Summary

Chapter III:

General Introduction

General Introduction

Since the dawn of history, man has sought to search for ways to hold on to life, which made the earth the first reference for the repertoire of living methods from the search for food, fire and wood to technology and energy, which led to a qualitative leap unparalleled in the world today, as he was not satisfied with that and went to the farthest limits and became fond of searching for energy sources on a large scale, not satisfied with surface wealth only but extended his view to the internal wealth of the earth. Fossil fuels also played a renaissance in the field of energy in the twentieth century. Still, its period of glory did not last long due to high consumption and reduced production, which revealed to the world the fragility of dependence on it. The situation deteriorated in the late twentieth century due to fuel residues and environmental pollution, which made researchers on a new search for renewable energy sources.

Among the promising solutions in the field of sustainable energy is the Earth–Air Heat Exchanger (EAHE), which plays a vital role in natural heating, ventilation, and air conditioning systems. This system exploits the relatively stable temperature of shallow underground layers to precondition the air, thereby reducing the reliance on conventional electrical energy sources. It offers an efficient and eco-friendly method for improving indoor comfort, especially in regions with harsh environmental conditions. However, the performance of the EAHE system is influenced by several complex factors—environmental, structural, and operational—making its modeling and analysis a challenging task.

In parallel with these developments, the rapid growth of digital technology has significantly impacted the scientific and engineering landscape. Artificial intelligence, particularly deep learning, has proven effective in solving complex problems and enhancing system efficiency across various fields. Deep learning models are capable of recognizing patterns in large datasets and making accurate predictions, which makes them highly suitable for thermal applications. In this context, our work focuses on applying deep learning techniques—specifically Convolutional Neural Networks (CNNs)—to model and predict the performance of Earth–Air Heat Exchangers. This approach aims to overcome the limitations of traditional modeling methods and provide a reliable predictive tool that contributes to the improvement of system design and energy efficiency.

The first chapter begins with a general study of the geothermal heat exchanger and its mathematical formulation, then passes through its most important physical properties and the factors affecting them, and concludes with the most important areas of its applications.

In the second chapter, we conducted a general study on artificial intelligence and artificial neural networks, as well as discussed convolutional neural networks and their components, and concluded with their mechanism of action.

In the third chapter, we discussed the geographical area to be worked on and then presented and analysed the results obtained.

Chapter I:

Earth-air heat exchanger and mathematical modelling

I.1 Introduction:

Geo-air heat exchangers (EAHE) are one of the latest renewable energy systems that have gained popularity in the last decade and are considered by researchers to be the torch of the future It is one of the most prominent sustainable energy technologies that sought to take into account the environmental balance and reduce the use of traditional devices and has shown effective results in air conditioning using geothermal energy, benefiting from the stability of ground temperatures throughout the year. This type of system requires many studies of the design structure, from the characteristics of the soil and climate to the materials and pipes used, In this chapter, we will address the historical development of geothermal heat exchangers, through the characteristics of its basic components, identifying its different types and forms, and ending with a study of the most important variables that affect its productivity. We will also highlight the place of this system in the framework of globally adopted green energy systems, based on the criteria of sustainability and energy efficiency.

I.2 Historic :

Ancient and Pre-Modern Era :

Ancient Persia (now Iran) relied on an advanced architectural cooling system that was ahead of its time, based on underground canals where water travelled from underground to the surface using natural gradient without the need for energy. These canals contributed to the natural cooling of the air, as air currents passed through cool, moist underground tunnels, reducing the temperature in hot climates and then utilising this air to cool buildings and save water [1].

Figure I.1: Persia Natural Heat Exchanger

Roman Hypocausts:

The Roma had a special sophisticated heating system called Hypocaust. In this system, they exploited underground voids to raise the air temperature. The mechanism involved heating the air with furnaces and then directing the heated air to flow through voids under the floors of hollow buildings and through channels inside the walls, ensuring a natural and balanced heating of the buildings [2].

Figure I.2: Roman Natural Heat Exchanger

Arab

Most Arab countries are located in desert areas, a difficult environment and a hot and dry climate, which made them build their homes in the middle of mountains, caves and caverns to shelter from high temperatures, as they are characterized so that the outer shell of the building (envelope) is in direct contact with the surrounding soil or rocks. This direct contact with the ground contributed to regulating the temperature inside these houses and creating a more stable and comfortable indoor environment without the need for industrial cooling systems [3].

Figure I.3: Arab Natural heat exchanger

1930s-1940s: Geothermal Research:

This period is considered to be the starting point for the development of geothermal heat exchange systems, as researchers turned to geothermal energy and heat pumps as a starting point for this type of sustainable system. [4]

1980s-1990s: Formalization of EAHE Systems:

Air-Earth Heat Exchanger (EAHE) systems have undergone a remarkable evolution towards greater organization and practicality. Researchers have focused on rigorously studying the thermal performance of these systems and optimizing their design to suit climate variations in different geographical regions. Efforts have also focused on improving construction techniques and efficient resource utilization, making these systems more efficient and applicable to sustainable heating and cooling projects [5].

In the 21st century, researchers have carried out extensive theoretical and empirical studies aimed at enhancing the performance of Earth-Air Heat Exchanger (EAHE) systems. These efforts have focused on identifying and analyzing the key factors influencing system efficiency, often utilizing advanced simulation tools and computational models to optimize design and operational parameters under various environmental conditions [6].

I.3 Earth-Air Heat Exchangers:

Geo-air heat exchangers, also called Canadian wells and Provençal wells, One of the most prominent sustainable energy systems are active ducts (for heating/cooling) in buildings. More precisely, they represent a network of pipes buried underground at a certain depth that allows air to flow through them. [7]

The mechanism of action is based on a simple physical principle of transferring the temperature of the subterranean soil to the pipe until a thermal balance occurs between them, creating a kind of natural ventilation (heating/cooling).This is where the constant year-round temperature of the Earth comes into play. In summer, the earth's temperature is cool and the surface is hot, resulting in the cooling of the air inside, while in winter, the earth's temperature is warmer than the surface, resulting in the heating process.

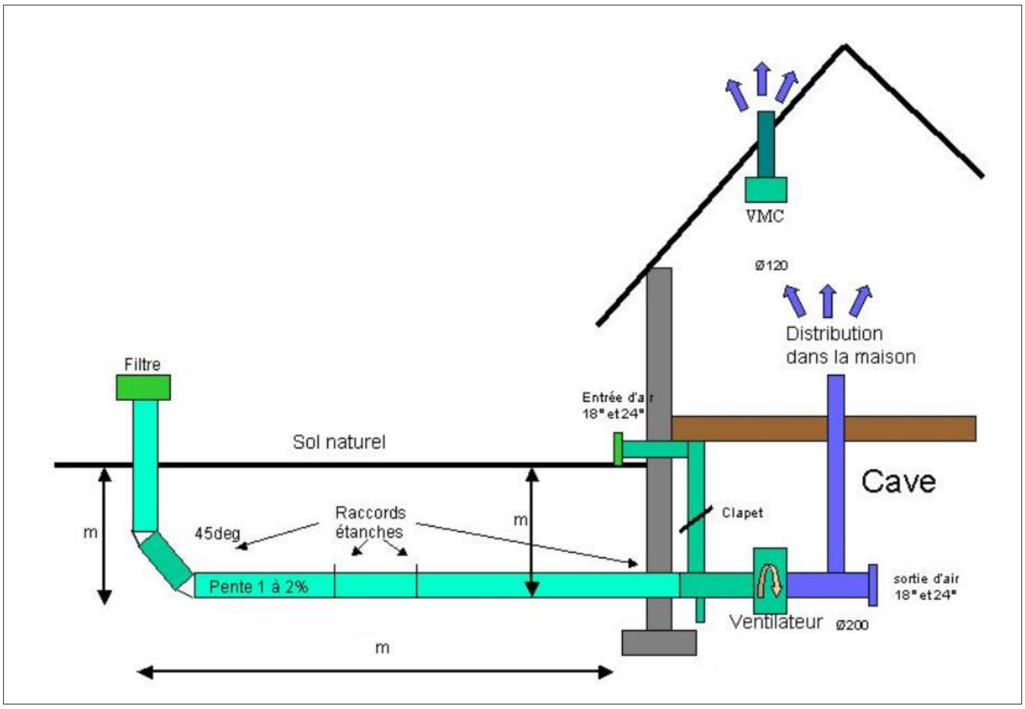


Figure I.4: Earth-Air Heat Exchanger Diagram [8]

This system has been awarded LEED certification for meeting global sustainability standards such as energy efficiency, longevity, and environmental friendliness, which has incentivised countries to support this type of system.

I.3.2 Characteristics of the main components of an air-to-ground heat exchanger:

One of the key factors that has encouraged investment in geothermal heat exchanger systems is the simplicity of the design, making it easy to implement**.**

The components of the system are as follows: [9]

Air Inlet: is a pipe elevated more than 1.10m above the ground, often the same size as the pipe it is connected to, with a protective cover and a filter to filter the air and prevent rain from entering.

Tube specifications:

Number of tubes :The number of pipes depends on the type of system and may consist of a single pipe or a network of parallel pipes

Length of tube :The duct length is set based on the required airflow rate and soil type. Studies have shown that 30 to 50 m is the ideal length.

Tube diameter :The airflow velocity between 1 and 3 m/s is the optimal value, and depending on this, the appropriate diameter is selected .

Tube layout: It is advisable to limit the number of elbows, to minimize compression losses, and facilitate maintenance.

Tube depth: Depth is chosen depending on soil temperature, topography, and construction cost. The recommended depth is often between 1.5 and 3 meters

Spacing between tubes: To ensure good heat exchange, the spacing between the tubes should preferably be three times the diameter.

Duct slope: When warm outdoor air comes into contact with the cooler walls of the column, condensate may form, and to promote its drainage, a slope of between 1 and 3% is preferred .

Tube material :Materials have a direct impact on heat exchange as walls with high thermal conductivity and resistance to burial are often used and are generally made of flexible or rigid PVC, polyethylene, or polypropylene.

Blower/Fan: A fan is used to regulate the speed of airflow [10], often two fans are used, one at the inlet and one at the outlet to distribute the air inside the building.

I.3.3 The types of air/soil heat exchangers:

There are two types of air/soil heat exchangers:

Open System :

The most commonly used open system, as shown in Figure 03, air is introduced by a turbine through pipes from the outside environment and is then (cooled/heated) by heat exchange with the soil and connected to the building. [11]

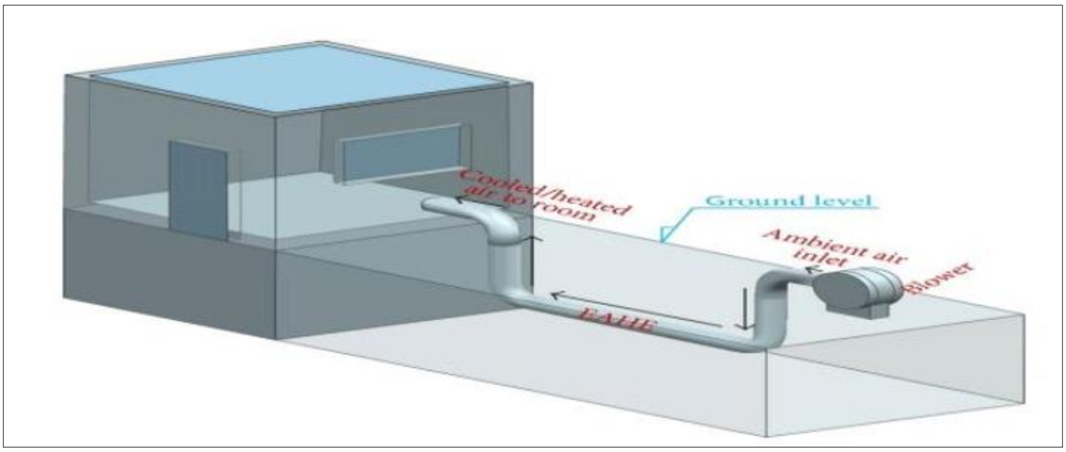


Figure I.5: Open EAHE System

Closed System:

In the Closed system shown in Figure 04, the air from the building enters the pipes, passes through the soil, and then returns to the building [11].This type of system is resorted to in case of low outdoor air quality such as industrial areas and in case of excessive heat and humidity and also to maintain constant pressure or humidity in hazardous industries such as pharmaceuticals, laboratories or operating theatres because it is characterised by maintaining accurate air conditions without sudden change due to external air.

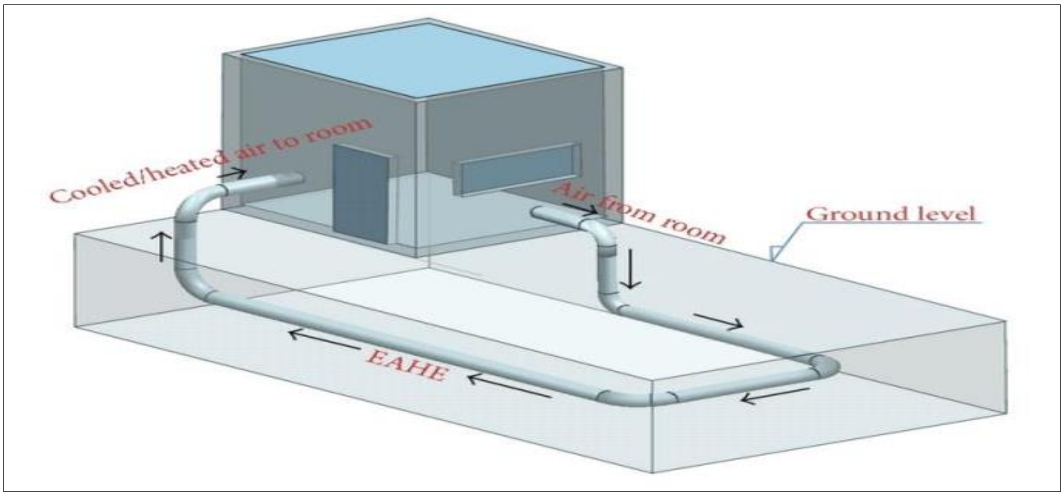


Figure I.6: Closed EAHE System

I.3.4 Forms of the air/soil heat exchanger system:

Horizontal air/soil heat exchanger:

In Horizontal Earth-Air Heat Exchanger, it is a closed-loop system, the pipes are connected in series or parallel. It is more commonly used in large areas as it facilitates digging the trench at a lower cost [12].It is characterised by lower excavation costs, easier and safer installation and maintenance, more effective with wet or clay soils, and the ability to integrate with conventional ventilation systems.

Figure I.7: Horizontal EAHE [13], [14]

Vertical air/soil heat exchangers:

The BHE, also called a borehole heat exchanger, is characterized by the vertical installation of pipes with a depth of more than 10 meters, suitable for smaller spaces and more efficient due to the temperature stability at that depth [15] , and is protected from environmental factors. It is not affected by sunlight or surface changes and avoids tree roots, surface pits or water leaks, and is most effective in large and complex buildings and systems.

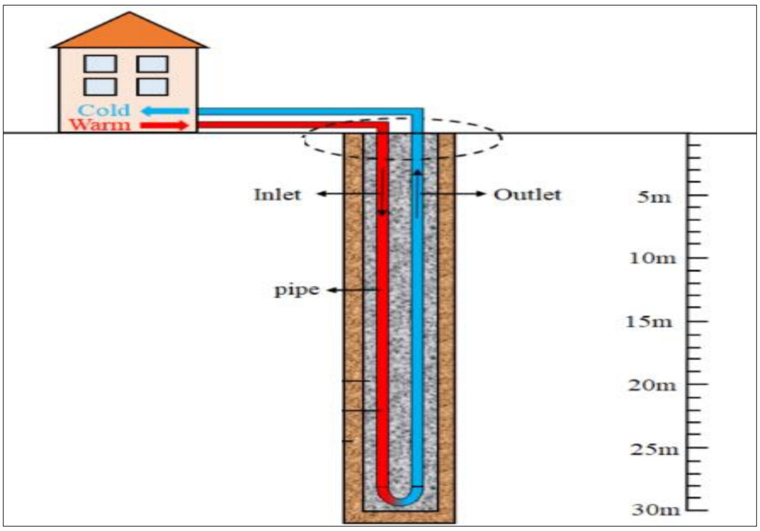


Figure I.8: Vertical EAHE [16]

Spiral EAHE:

It is Compact Design this design is based on a double helical tube structure characterized by a larger surface area and diameter, which gives a higher thermal capacity [17].Lower cost than a vertical system as it does not require deep drilling or heavy equipment and is a flexible design where the number of coils or the depth of the hole can be adjusted as needed.

Figure I.9: Spiral EAHE [18], [19]

I.3.5 Factors Influencing the Performance of Earth Air Heat Exchangers

The idea of structuring the system, although simple, requires a number of factors to be taken into consideration as they have a direct impact on the effectiveness of the system

I.3.5.1Soil properties: Heat transfer depends on the inertia of the soil and its physical (physical and chemical) properties. The main factors of soil properties are highlighted as follows: [20]

Heat Capacity: is the amount of heat needed to raise the temperature of an object by a certain amount, symbolized by C_s

$$\boldsymbol{C_s = \sum X_i \rho_i C_i}$$

- $\boldsymbol{X_i}$ **-** The mass fraction or volume fraction of component i*i* in the mixture.
- $\boldsymbol{\rho_i}$ - The density (if $\boldsymbol{X_i}$represents the volume fraction)
- $\boldsymbol{C_i}$ - The specific heat capacity of component *i*

Thermal Conductivity is the rate at which heat energy is transferred through a material due to a temperature gradient. The higher the coefficient of thermal conductivity, the more significant the material's ability to transfer heat.

Thermal Diffusivity $\boldsymbol{\alpha_s}$**:** Thermal diffusivity describes how fast a material's temperature changes when exposed to a change in heat.

I.3.5.2Climatic Surface:

It is the interface between the earth (soil) and the atmosphere, where climate variables

Climate variability directly affects the earth's surface and thus the soil undergoes changes throughout the year, affecting the system EAHE

I.3.5.3Physical properties of pipes: These parameters (length, diameter, material, number and distance between pipes) are the most important factors affecting the performance of the system, as they control the airflow velocity and heat exchange area and protect it from corrosion, etc.

I.3.6 Modeling EAHE

The EAHE model was developed to extract the maximum amount of cold energy present in the first few meters underground at a lower financial cost [21].

To simplify the mathematical model, we consider the assumptions most commonly used in this type of problem. We assume that : [22]

- The flow of the fluid (air) is considered laminar, Newtonian and incompressible along the entire duct length..

- Heat exchange is steady state.
- The soil surrounding the pipe is homogeneous and isotropic, with homogeneous thermal conductivity in all soil layers..
- Assuming that the tube temperature is equal to the ground temperature.

Tsol = Ttube

- There is no chemical reaction and no source of heat or mass.
- Heat transfer by radiation is negligible.

I.3.6.1 Modeling of soil temperature:

Inertia maintains a near-constant soil temperature year-round.A slow change in soil temperature leads to the formation of a sinusoidal function, based on the theory of thermal conductivity applied to a quasi-homogeneous solid. The following differential equation expresses this: [23]

$$\frac{\partial^2 T}{\partial Z^2} - \frac{1}{\alpha} = 0 \quad (1)$$

Where $\boldsymbol{\alpha} = \frac{\lambda_{siol}}{\rho C_{siol}}$

- α is the soil thermal diffusivity in $m^2\ S^{-1}$
- z is the depth below ground surface
- $\lambda_{siol}$is the soil thermal conductivity expressed in $Wm^{-1}°C^{-1}$
- C_{siol} is the soil specific heat in $J\ kg^{-1}°C^{-1}$
- ρ is the soil density in kg m^{-1}

The corresponding boundary conditions at z =0 were the following:

$\boldsymbol{T(0,t)} = T_{surface} = T_{mean} + \mathrm{A}\cos[\omega(\mathrm{t} - t_0)]$

(2)

and for the infinite depth $Z \to \infty, T(\infty, t) = T_{mean}$

$\boldsymbol{T(z,t)} = T_{mean} + \mathrm{A}\left(\mathrm{Exp} - (\mathrm{z})\sqrt{\pi/365\alpha}\right) \times \cos\{\frac{2\pi}{365} \times (\mathrm{t} - t_0) - (z/2) \times \sqrt{365/\pi\alpha}\}$

(3)

I.3.6.2 Earth model development

In this work, the thickness of the annulus is taken as being equal to the pipe radius [24], [25]:

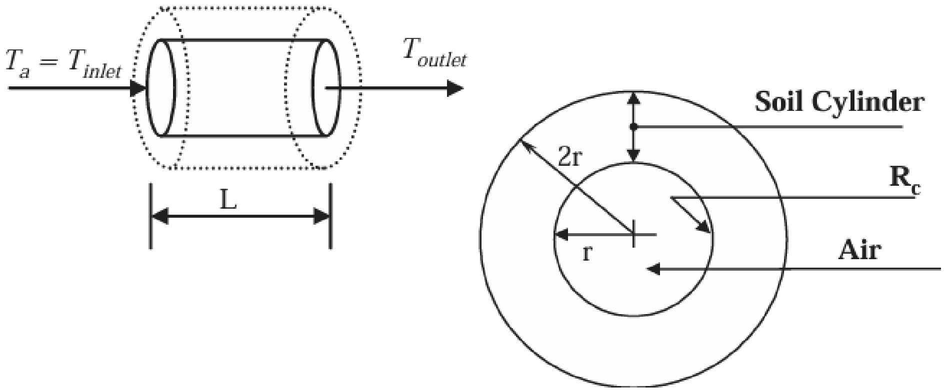


Figure I.10: Illustration of tube variants

The heat transfer along the buried pipe is calculated by:

$$\emptyset = \dot{m} C_{pf} dT(x) = \frac{dx}{R_{conv}+R_{pipe}+R_{soil}} (T(z,t) - T(x)) \tag{4}$$

The thermal resistance of the pipe is expressed by:

$$\boldsymbol{R_{pipe}} = \frac{1}{\lambda_{pipe} 2\pi} Ln(r_e/r_i) \tag{5}$$

- $\boldsymbol{\lambda_{pipe}}$ - the $pipe$ thermal conductivity expressed in $Wm^{-1}{}^{\circ}C^{-1}$
- $\boldsymbol{r_e}$ - pipe radius(m)
- $\boldsymbol{r_i}$ - radius of cylinder denoting thickness of soil surrounding pipe(m)

The thermal resistance of the soil is calculated by:

$$R_{soil} = \frac{1}{\lambda_{pipe} 2\pi} Ln(R_{(z,t)}/r_e) \tag{6}$$

- $\boldsymbol{\lambda_{soil}}$ - the $pipe$ thermal conductivity expressed in $[Wm^{-1}{}^{\circ}C^{-1}]$
- $\boldsymbol{r_e}$ - pipe radius[m]
- $\boldsymbol{R_{(z,t)}}$- Effective external radius of the soil.

The convective the rmal resistance on the inner surface of the pipe is:

$$\boldsymbol{R_{conv}} = \frac{1}{r_i h_{conv} 2\pi} \tag{7}$$

Where h_{conv} is the coefficient of heat transfer by convection in a tube, is defined by:

$$\boldsymbol{h_{conv}} = \frac{Nu\, \lambda}{D} \tag{8}$$

The following correlation expresses the number of Nusselt:

$$\boldsymbol{Nu} = 0.0214(Re^{0.8} - 100)Pr^{0.4} \tag{9}$$

The Reynolds and Prandtl numbers inside the tube are calculated by:

$$\boldsymbol{Re} = \frac{V_{air}\, D}{v} \tag{10}$$

$$\boldsymbol{Pr} = \frac{v\,\rho CP}{\lambda} \tag{11}$$

- **D** - Pipe diameter [m]
- $\boldsymbol{V_{air}}$ - Average air velocity inside the pipe [m/s]
- **ν** - Kinematic viscosity [m^2/s]
- $\boldsymbol{\rho}$ - density of air [kg/m^2]
- **Cp** - Specific heat capacity [J/(kg·K)]

The total heat transfer coefficient of the EAHE is given as:

$$\boldsymbol{G_{Tot}} = \frac{1}{(R_{conv}+R_{pipe}+R_{soil})} \tag{12}$$

By combining equations (4) to (12), the energy balance reads as follows:

$$\frac{dT(x)}{T(z,t)-T(x)} = \frac{G_{Tot}}{\dot{m}Cp}dx \tag{13}$$

Integrating equation (16) is then:

$$-L\big(T(z,t) - T(x)\big) = \frac{G_{Tot}}{\dot{m}Cp}x + Cte \tag{14}$$

I.3.7 Applications:

In Building Residential and Commercial:

It is often adopted in residential and commercial buildings as it helps to minimize electricity consumption [26]. The EAHE system reduces energy consumption, especially in closed spaces, improves indoor air quality because it contains filters to filter the air, reduces the load on cooling and heating devices, which is accompanied by a reduction in consumption and maintenance costs, and is considered a profitable deal for commercial buildings and hotels because it maintains an ideal temperature despite the size of the space, and is regarded as the main pillar in green buildings as it ensures improved energy performance and meets international sustainability standards such as LEED certification.

Figure I.11: Hybrid system building

Industrial applications:

Power plant cooling through floor cooling , Increased productivity and minimized
material spoilage [26] . Its role in the industrial sector has emerged in maintaining the performance of equipment and product quality, especially in the food industry and electronics where it requires a constant temperature, as it can be used in data centres and servers as it is a heat-intensive environment that needs to reduce the energy load, and it is ideal for the chemical and pharmaceutical industry as it keeps the air clean by filtering the air entering it. Contributes to a comfortable environment for workers.

Figure I.12: Heat exchanger plant

Agricultural applications:

This system has helped to increase production and provide off-season
produce by providing a favorable environment for the plants [27].
Greenhouses help provide optimal humidity and temperature for plant growth, which contributes to providing the product throughout the year, increasing yield and improving crop yields,Poultry farms and livestock sheds to provide a suitable environment for animals, which

corresponds to an increase in animal production,Storage centres for grains and fruits, which reduces the risk of spoilage, which is called sustainable agricultural practice.

Figure I.13: Greenhouses with heat exchangers

It is also used to cool data centers and solar panels, and researchers have integrated it with various renewable energy systems.

I.4 Conclusion

We have highlighted in this chapter that geothermal heat exchangers, despite the simplicity of the physical law that governs them, are a complex design that requires planning and a careful approach to ensure the effectiveness of the system. This technology is not just a solution for sustainable air conditioning, but a strategic approach towards a clean energy future, so researchers must expand efforts to increase the efficiency of the system.

Chapter II:

Artificial Intelligence and Convolutional Neural Network, and Artificial Neural Network

II.1 Introduction:

Artificial Intelligence (AI) is one of the prominent fields in the modern era and has been highly acclaimed by researchers, as it has a great role in the development of research, as it has a new methodological pattern that adopts a different approach to the study of research problems, and one of the fields that has not been spared from AI is Earth geology, as heat exchangers have had a share in the technological renaissance

II.2 Artificial Intelligence

II.2.1 Definition of Artificial Intelligence

Developers differed on the definition of artificial intelligence and how it works, but they were united on one idea :Is a computer system able to perform tasks that normally require human intelligence [28] . The concept of artificial intelligence is summarised in three overlapping terms

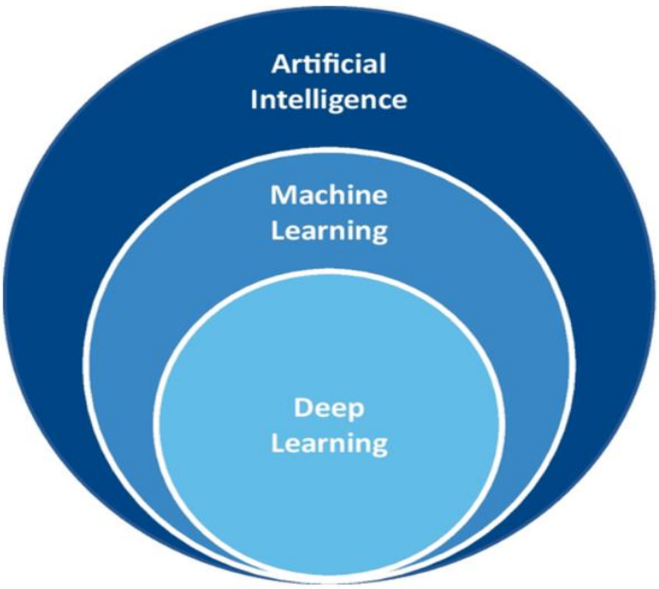


Figure II.1 : Artificial intelligence system [29]

Machine Learning is an advanced artificial intelligence technique that uses computer models to study data patterns, make decisions based on them and automatically optimise their performance with experience, without having to be explicitly programmed for each task [30]

Deep learning is a special type of machine learning that achieves high power and flexibility [31]utilising a layer of neural network that relies on statistical prediction to make decisions

Thus, we find that Artificial Intelligence outperforms the human brain in calculations, speed and accuracy, but fails in other aspects such as recognising objects, shapes and solving everyday problems and is mainly dependent on the database provided, which makes us address the types of education in Artificial Intelligence .

II.2.2 Types of Machine Learning:

Supervised learning:

It is a type of machine learning that relies on algorithms to categorise real-world data and extract patterns and relationships between them to make accurate predictions. Supervised learning is used in many areas of life, such as weather forecasting, temperature and pressure changes, and is also exploited in the study of the market and price changes [32]

Unsupervised Learning:

A type of machine learning that learns from data without human supervision, Used to make inferences from data sources made from unlabelled responses to input data [33]

Reinforcement Learning:

is a specialized area within the broader field of machine learning that focuses on how agents can take actions in an environment to achieve specific goals. In reinforcement learning, the agent learns through trial and error, interacting with its surroundings and making decisions based on the outcomes of its actions. This process involves receiving feedback in the form of rewards or penalties that help guide the learning process.

II.3 Artificial Neuron:

An artificial neuron acts as a connecting unit within an artificial neural network. Like biological neurons, it processes incoming signals and passes outputs to other nodes in the network. These nodes are commonly called neurons, and their connections are defined by synaptic weights, which indicate the strength or importance of each link. As new inputs are received and analyzed, these synaptic weights adjust, enabling the network to learn and adapt. [34].

II.4 Artificial Neural Network(ANN):

II.4.1 Definition of Artificial Neural Network

It is a set of algebraic functions and calculations with a structure similar to the human brain, capable of learning patterns and building models based on input data, consisting of a set of interconnected nodes, arranged in layers that process the input data by weighted connections and activation functions to produce outputs [35].

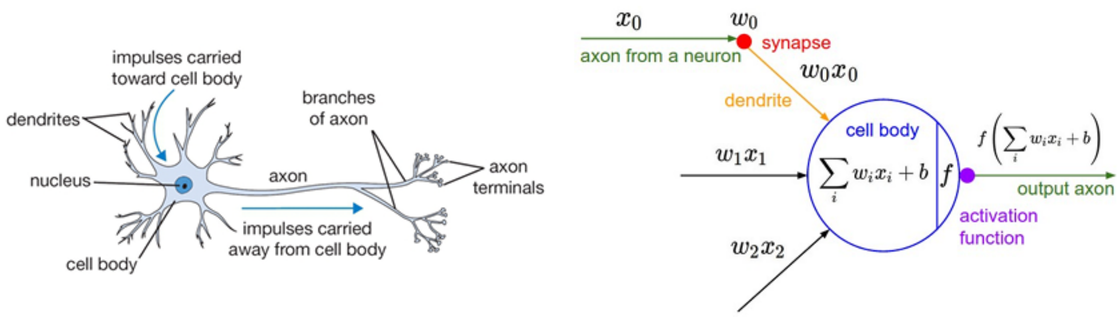


Figure II.2: Human and Artificial Neural Networks [36]

II.4.2 Working principle

_Dense layers are made up of interconnected neurons.

_Each neuron from one layer is connected to every neuron in the next layer.

_Each connection between neurons has a weight associated with it, which is a trainable factor.

This weight is multiplied by the input value.

_They are summed up and a bias is added, which is another trainable factor. The purpose of the bias is to compensate the outputs positively or negatively.

Finally, each cell's output passes the activation function that determines the output of the last [37]

$$Y = X * W + B$$

forming a linear function with slope x and y-intercept B

With:

Y=Output ;X=Input ;W=Weight ;B=Bias

Each cell passes its results through the given function before

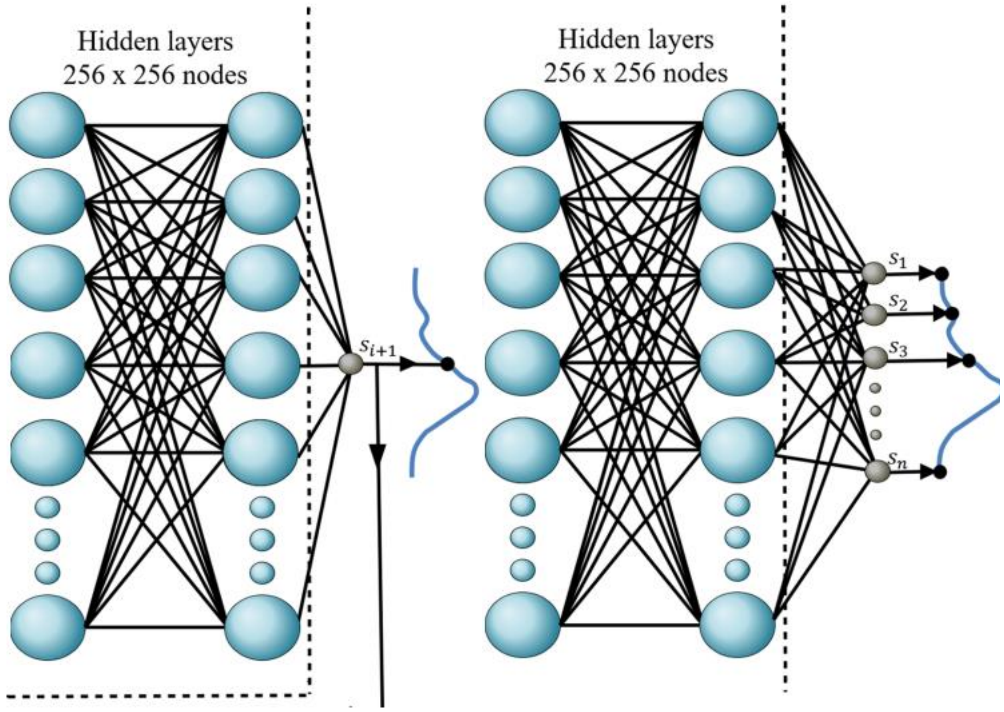


Figure II.3: Artificial Neural Network mechanism [38]

outputting its final value

II.4.3Type of Activation function:

Threshold Function

Also called the Heaviside function, it is one of the simplest activation functions and is only used in binary classification (0/1). Its terms are expressed as

$$S(x)\begin{cases}1 & if\, x \geq 0\\ 0 & if\, x < 0\end{cases}$$

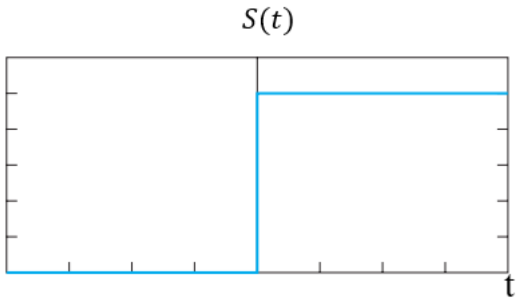


Figure II.4: Threshold Function

Sigmoid Function:

An x-shaped mathematical function, the most commonly used activation function due to its ability to smoothly transition from linear to non-linear, is often used in binary classification. The following formula expresses it:

$$\boldsymbol{S(x) = \frac{1}{1 + exp^{-x}}}$$

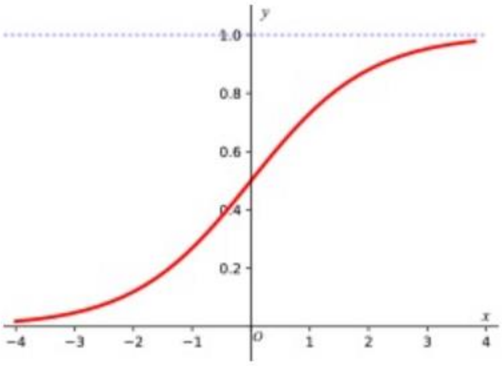


Figure II.5: Sigmoid Function [39]

Hyperbolic Tangent Function(tanh):

It is a mathematical function that is also used to activate the Sigmoid by challenging the inputs from [-1,1], which helps to centre the data and improve convergence. It also helps to introduce nonlinearity and is mathematically expressed as:

$$\tanh(\mathrm{x}) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^{x} - e^{-x}}{e^{x} - e^{-x}}$$

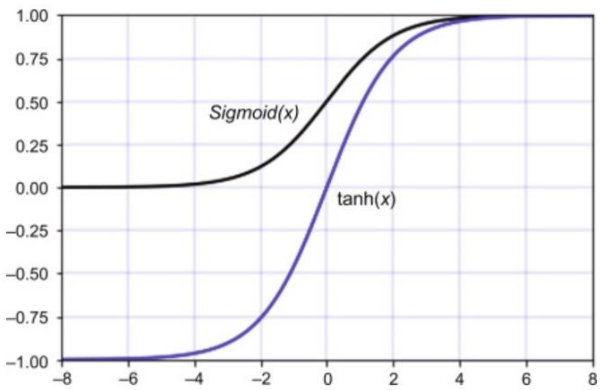


Figure II.6: Hyperbolic Tangent Function [40]

Rectified Linear Unit Function (ReLU):

It is one of the most commonly used functions, often as an activation function in hidden layers, and its mechanism lies in converting negative values to 0 and outputting positive values as they are, which helps avoid gradient fading issues, and is characterised by fast calculations, making it easy to train. One of the most common issues affecting deep learning with this function is that if most of the values are negative, it results in an imbalance, and most of the weights will not play an effective role. It is expressed mathematically as

$$\mathbf{ReLU}(\boldsymbol{x}) = \max(\mathbf{0}, \boldsymbol{x})$$

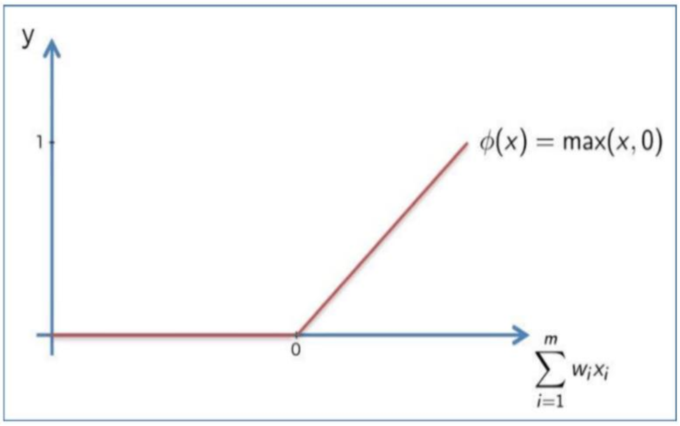


Figure II.7: Rectified Linear Unit Function [41]

Leaky ReLU Function:

It is a modified version of the Rectified Linear Unit Function that solves the issue of converting all negative values to zero and preserves some gradient in the negative values as follows:

$$\mathbf{Leaky\ ReLU} = \{ {}^{\mathbf{x\ \ if\ x > 0}}_{\propto\ \mathbf{x if\ x \leq 0}} \qquad \text{Often } \propto = \mathbf{0.01}$$

So

If we have a negative value, we multiply it by the alpha value, which reduces its value, so it is not eliminated, but we keep a small amount of it

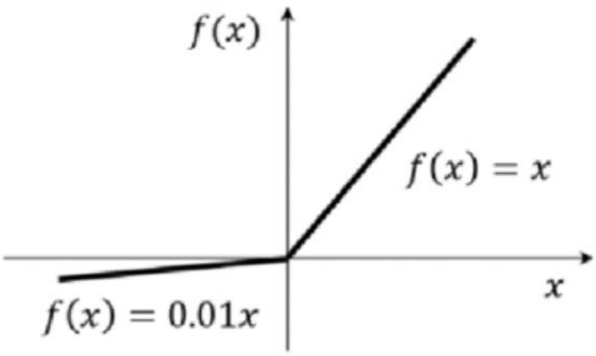


Figure II.8: Leaky ReLU Function **[42]**

Softmax Function:

It is a mathematical function that is often used in the final layers of a multi-class classification model. The working principle is to convert each value of x to positive using exponentiation and then divide it by the sum of all these values so that the result is between 0 and 1, thus forming a set of probabilities that sum to one.

$$Softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_i}}$$

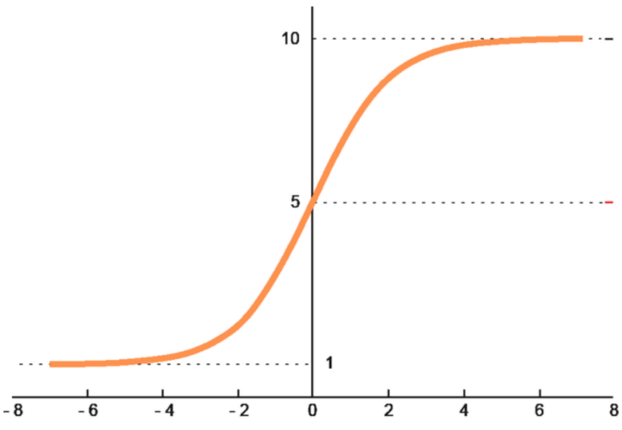


Figure II.9: Softmax Function **[43]**

Swish Function:

It is a non-linear mathematical function that is differentiable at all points and directly minimises negative values and, at very positive values, approaches the straight line

y=x. It is one of the most effective activation functions in deep learning

$$\mathbf{Swish}(\boldsymbol{x}) = \boldsymbol{x} \cdot \boldsymbol{\sigma}(\boldsymbol{\beta x}) = \frac{\boldsymbol{x}}{\mathbf{1} + \boldsymbol{e}^{-\boldsymbol{\beta x}}}$$

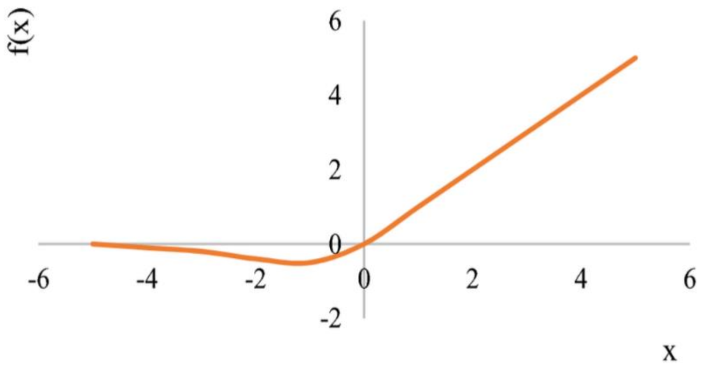


Figure II.10: Swish Function **[44]**

II.5 Convolutional Neural Network

II.5.1 Definition of Convolutional Neural Networks

It is a kind of neural network with a deep structure and containing a convolution calculation. Convolution calculation is one of the representative algorithms of deep learning architecture, which relies directly on analysing the input data using linear algebra to obtain patterns [45].

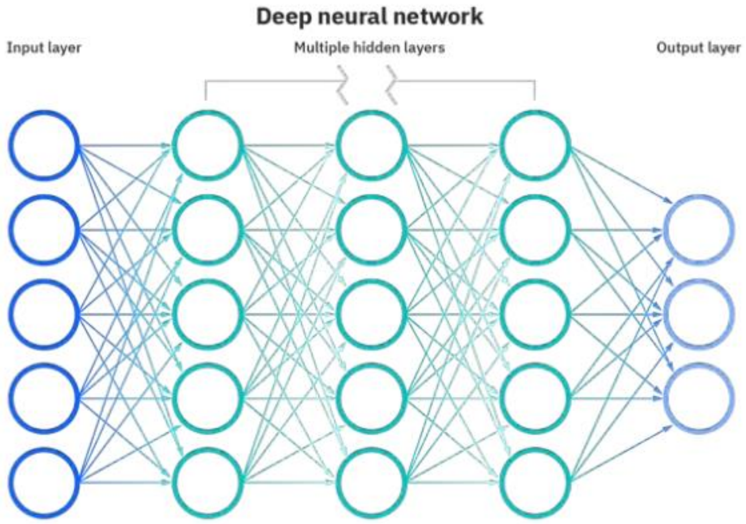


Figure II.11: Convolutional Neural Network [46]

II.5.2 Layers of convolutional neural networks [47]

Convolutional neural networks consist of three layers:

Convolutional layer:

It is responsible for most of the calculations and is the basic component of a neural network, and depends on(input data, a filter, and a feature map) ,The way it works is that each filter is associated with the input data, multiplies the values and produces what is known as a feature map, which helps the latter in detecting patterns, letters, etc. This is called the spatial hierarchy of features, where the process is automatic

Pooling Layer:

It is a layer in a Convolutional Neural Network**.** It aims to reduce the spatial dimensions of the feature maps, while keeping the most important information using maximum clustering (operates by computing the average value of the rectangular region surrounding the central pixel)There are two types of grouping

Maximum aggregation: Clustering is a type of clustering used in the input feature map whose role is to retain the most important features by taking the maximum value from each region, i.e. minimising spatial dimensions while preserving salient information and providing translation stability.

Average Aggregation: It is another type of clustering whose working principle is to calculate the value of each patch in the input feature map and thus calculate the average of all values in that region, characterised by preserving the more general features instead of only the strongest features .

Fully-connected (FC) Layer:

Also called the dense layer, it is usually located at the end of the neural network and collects all the features extracted from the previous convolutional and combinatorial layers (in the form of an activation volume) and transforms them into a probabilistic class vector, but with different MLP-like inputs that make it responsible for making the final decisions, such as classifying an image or predicting a value.

II.5.3 Convolutional Architectures

Stages in the evolution of convolutional neural networks**:**

CNNs (LeNet) [48]**:**

at the end of the 1990s, YANN LECUN and his colleagues developed the LeNet-5 convolutional neural network programme ,It was designed to process structured network data (handwritten number recognition - MNST data) .

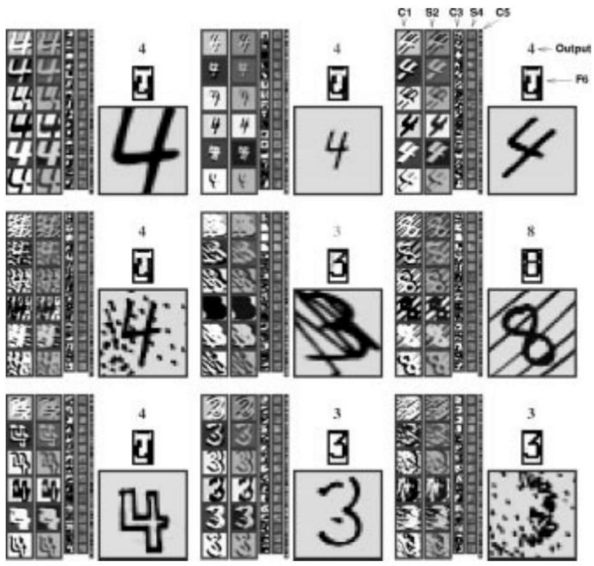


Figure II.12: Number Recognition Form

Deep CNNs [36]**:**

AlexNet: It is considered the beginnings of convolutional networks in computer vision. It focused on improving image recognition performance and achieved great success at the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)2012 with 26% higher accuracy (5).

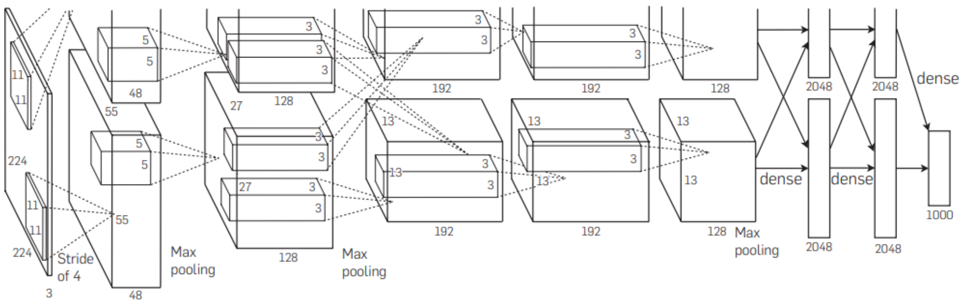


Figure 2.13:Architectural diagram of a convolutional neural network [49]

Very Deep CNNs [50]**:**

VeryDeep or VggNet**:**VGGNet**,** developed by the Visual Geometry Group at Oxford, introduced a novel convolutional neural network architecture that relied on many stacked layers with small 3x3 filters to achieve outstanding results on complex image classification tasks. Known for its intensive network design with increased depth, VGGNet brought attention to the importance of deeper layers for strong performance in computer vision domains. . VGGNet proved that substantial network thickness, obtained in a sensible design, unlocked superior interpretive proficiency on the enormously challenging ImageNet benchmark and sparked new directions for visual recognition models to follow.

GoogLeNet or Inception:GoogLeNet (a.k.a**.** Inception-v1**)** was introduced by Google researchers in 2014. It won the ILSVRC 2014 competition with a top-5 error rate of 6.67%**,** improving upon AlexNet (15.3%) and VGG (7.3%)**.** Its key innovation was the Inception Module, which enabled efficient computation and deeper networks without excessive parameters.

Residual CNNs [51] **:**

Introduced by Kaiming He and his colleagues at Microsoft Research in 2015, a groundbreaking breakthrough in deep learning was achieved with the presentation of ResNet (Residual Networks). , ResNet's pioneering architecture demonstrated remarkable effectiveness in image classification tasks, culminating in a top-5 error rate of just 3.57% during the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2015. This performance not only surpassed previous state-of-the-art results but also exceeded human-level performance, estimated at around 5%.

II. 5.4 Training Deep Learning Model [52]*:*

Creating a deep learning model requires a lot of precision, as each stage has an exceptional role that cannot be bypassed.

a.Prepare Dataset:

This stage has a significant impact on the model as the more data you have, the more accurate the results will be. Data is divided into three types:

_ The training set, which is often 80% of the total data and is used for learning weights and biases. **_**The second set is the investigation set, which represents 10% of the total set and is used to optimise the training and control of the network.

_ The third set is the test set, which also represents 10% of the total set. This set aims to evaluate the performance of the model, and it is required that this data be from the real world to make the model more interactive in daily life.

Each group must be completely independent of the others so as not to backfire on the model

b.Data Augmentation:

It is a way to multiply data by

_Geometric transformation: Manipulating the position of the image horizontally, vertically or diagonally.

_Colour manipulation: lowering and raising the luminosity, brightness, colour grading and saturation.

_Generating artificial data: using artificial intelligence tools to create images.

All this in the context of data augmentation and diversity, which contributes to increased recognition in the results.

c. Create the Model:

Depending on the goal (language processing, image recognition), a deep learning model is created that determines the final model function, such as the loss function, cost function, etc.

d. Training the Model:

This is the core of deep learning, where we continuously change the weights and biases, leading to a change in values to minimise error and maximise prediction accuracy.

e. Model Evaluation:

Model evaluation is as important as the other phases and depends on the type of task the model is trying to solve. It is responsible for studying the performance of the model and trying to obtain the best results, often the loss function being the most effective in evaluating performance.

f. Model Optimization:

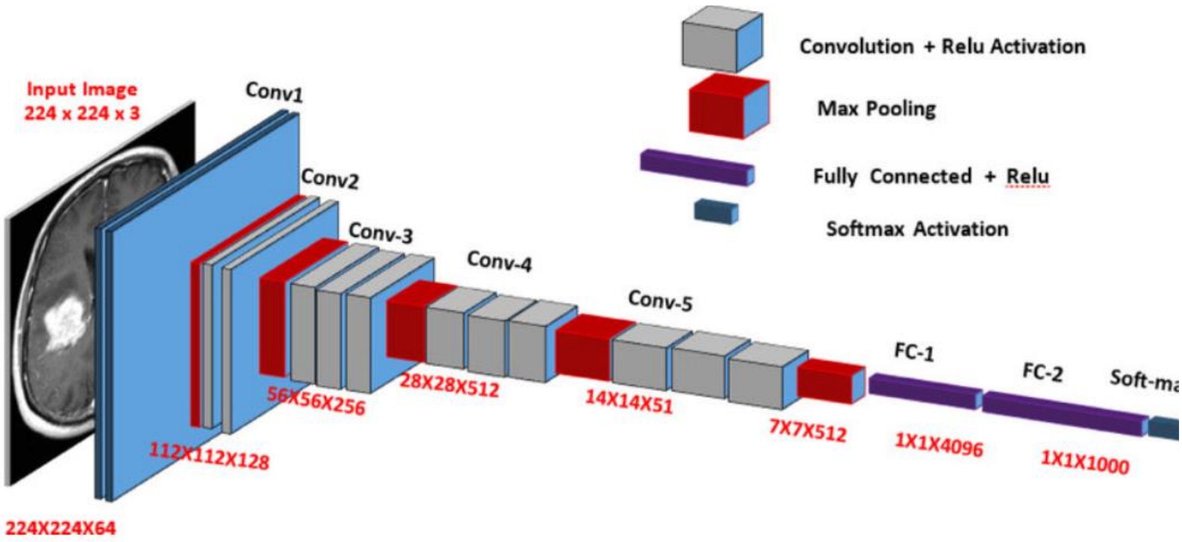
At this stage, the performance of the deep learning model needs to be optimised by measuring the difference between the desired (measured) results and the expected output results, and depending on this, changing the weights and biases to minimise the incoming error rate.

g. Model Deployment:

Publish the model and present it to users with a continuous endeavour to improve it between intervals.

II.5.5 Architectures of VGG

The architecture of this model was announced in 2014 by the University of Oxford's Department of Optical Engineering and was widely popular at the time. The model is characterised by its simplicity and depth, making it more efficient. Its advantage lies in the use of very small (3×3) convolutional filters stacked in depth to increase network capacity while maintaining a manageable computational cost, and is based on a unified architecture where convolutional layers are followed by maximal aggregation layers and finally fully connected layers at the end.



Architectures of VGG Net [53]

II.6 Conclusion

Artificial Intelligence (AI) is a paradigm shift in the field of technology in all fields and has played an effective role in improving efficiency, reducing errors, accelerating decision-making and has had a pivotal role in analysing big data, predicting the future, and providing smart and sustainable solutions. It has shown a modern approach in developing studies and research, making it an essential tool in building a more advanced and innovative future.

Chapter III:

Discussion of simulation resul

III.1 Introduction:

The climatic fluctuations that the world has witnessed in recent years have had a direct impact on the performance of heat exchangers, which made the traditional method and mathematical equations less effective in keeping up with the age of speed, which required researchers to resort to artificial intelligence, specifically deep learning, as an effective means of modelling non-linear and complex relationships between different variables that affect system performance and has proven its effectiveness in providing accurate prediction of thermal performance based on operating conditions and environment. In this chapter, we discuss an experience in **Ghardaia** state where the models were fed with real data collected from the system in a certain period.

III.2 Ghardaia State - Geothermal Study Site:

The state of Ghardaia is the gateway to the Algerian desert, characterised by a dry and hot climate in summer and cold in winter, which makes it one of the most consuming cities for traditional cooling tools, which accompany energy consumption, but it has assets that may make it completely indispensable.

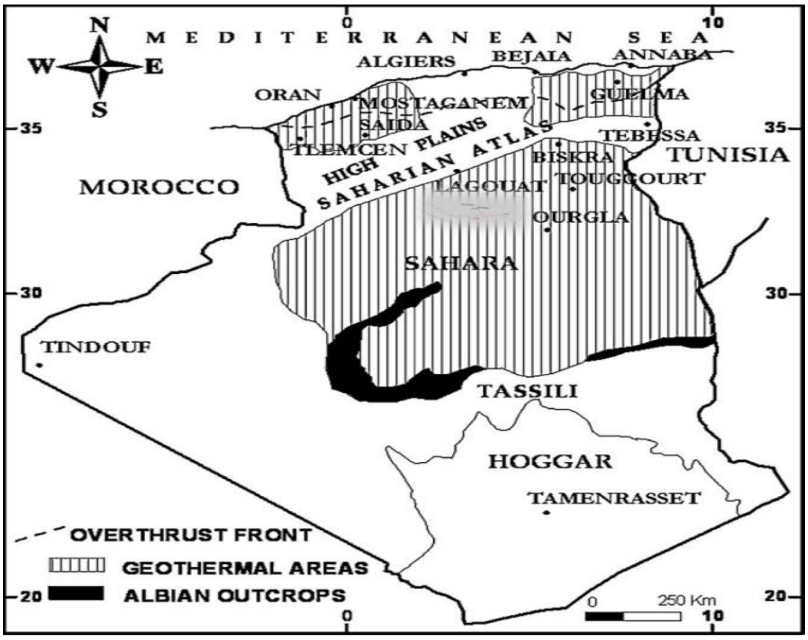


Figure III.1: Geothermal Map of Algeria [54]

Ghardaia is strategically located to study the effectiveness of geothermal heat exchanger systems as it is situated over sedimentary formations containing layers of sand, gravel and silt. These materials have high thermal conductivity and are characterised by the stability of soil temperature at certain depths (usually between 1.5 and 3 metres) where they tend to maintain a moderate temperature range between 22°C and 26°C throughout the year, providing suitable medium conditions to absorb or dissipate heat from air flowing through the buried pipes. The climatic and geothermal characteristics of the Ghardaia region provide a favourable experimental environment to evaluate the effectiveness of AI applications in predicting the thermal performance of EAHE systems in desert regions.

III.3 Objective of the pilot work:

This work consists of two parts:

The first part: We will compare two types of neural networks that were used in our study based on a database obtained in a specific period. The first type is feed-forward backpropagation, while the second type is feed-forward cascade backpropagation. In this section, we will discuss the main differences between these two types of networks and how these differences affected the results of our study.

The second part: We will use convolutional neural networks to build a predictive model on a database obtained in a specific period.

III.4 Experimental Setup:

Using MATLAB R2015a, we created training models for artificial neural networks to predict the temperature of the air exiting the Earth-Air Heat Exchange (EAHE) system, using a set of climate variables as inputs.

MATLAB :

In this study, MATLAB R2015a was used. This version was released in March 2015 by MathWorks with a supported operating system for Windows, macOS, Linux and the MATLAB programming language (M-code) that contains the most essential libraries to support the Neural Network Toolbox for modelling neural networks (ANNs)

Input and output data

We have four basic inputs to the model: time (t), the temperature of the incoming air (Tin),

the relative humidity of the incoming air (RHin), relative humidity of the outside air (RHout).

The outdoor air temperature (Tout) is also considered as an output of the model.

Network Architectures

We use two types of networks:

Feed-forward backprop: In the first study, we rely on this cell type where the network has one simple hidden layer with multiple neurons from 5 to 150 in increments of 5.

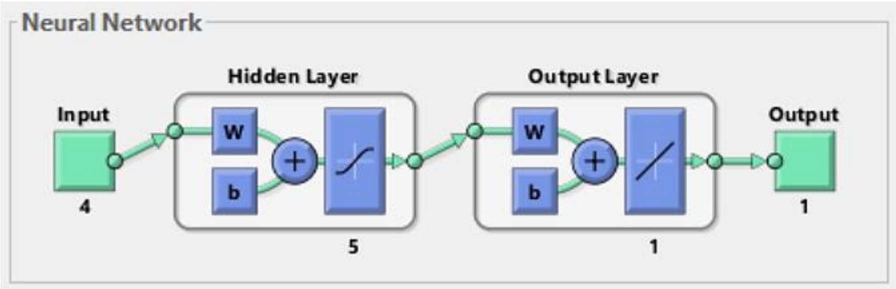


Figure III.2: Feed-forward backprop Network structures

Cascade-forward backprop: In the second study, we rely on this type of cell, which consists of two layers. The first layer contains several neurons from 5 to 150 in increments of 5. The second layer always contains a single neuron capable of connecting the inputs to all layers directly, to enhance the learning accuracy in some non-linear patterns.

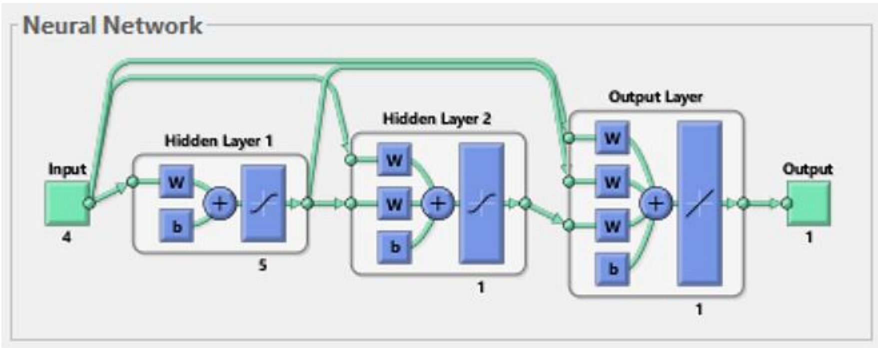


Figure III.3: Cascade-forward backprop Network structures

Functions used in the programme

The tan-sigmoid function (tansig) was adopted in the hidden layer and the linear function (purelin) in the output layer in order to ensure the continuity of network compatibility.

As for the training functions, the Levenberg-Marquardt algorithm (trainlm), which is known for its speed and efficiency in training small and medium-sized networks was used as the training criteria. We set 40 cycles as the maximum number of training cycles and 20 as the maximum number of successive verification failures.

Evaluation indicators

MSE and R are used as the main statistical indicators to test the performance of the model

Mean Squared Error – MSE: This indicator represents the average of the squares of the differences between the actual values of the target values (Actual Outputs) and the values predicted by the model (Predicted Outputs).

The Pearson R: correlation coefficient is used to measure the strength of the relationship between predicted and actual values. The closer the R value is to 1, the stronger the correlation between the predicted and actual outputs, so the model is considered to be accurate in prediction.

III.5. Artificial Neural Network(ANN)

III.5.1 Feed-forward Backpropagation:

a_The Pearson R^2:

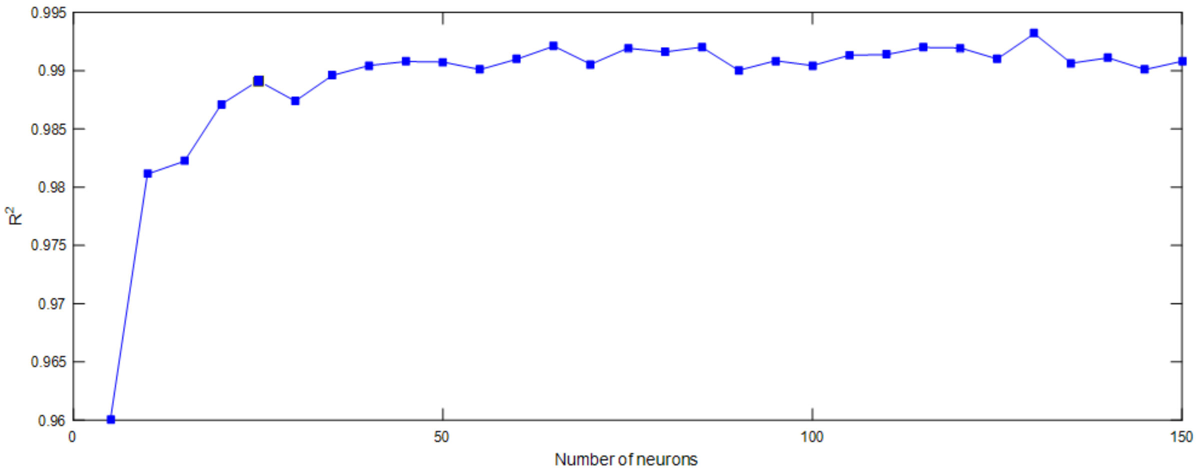


Figure III.4: The effect of the number of neurons on the model performance index R^2

The curve represents the relationship between the number of cells and the performance of the model measured using the coefficient of determination R^2, where we observe A decrease in the value of R^2 between 10 to 20 cells and then a rapid development with a value of about 0.985, which indicates the effect of increasing the number of cells to improve the performance of the model, after that the curve stabilises approximately between about 40 to 60 neurons, indicating the saturation of the model and its optimal performance. When the number of cells exceeds 60, we notice that this increase is useless and does not help improve the performance of the model, but rather leads to a slight oscillation due to the possibility of overfitting or oversensitivity .

b_MSE:

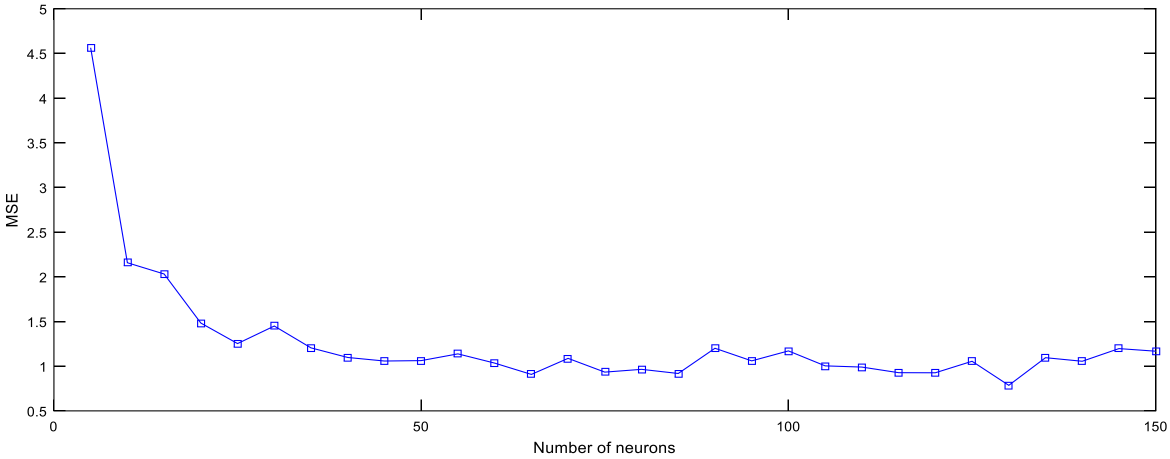


Figure III.5: Effect of Neuron Count on Mean Squared Error (MSE)

The curve represents the relationship between the number of cells and the error rates of the model, where we observe that the error rates peak around 4.5 and then start to decrease sharply when the number of cells exceeds 10-15, after which it continues to decrease with oscillation between 20-60 cells. When the number of cells exceeds 60. The curve begins to stabilise, approaching a minimum value of around 1.0-1.2.

Results:

When analysing the two curves $R^2$and MSE, we find that the best range of model performance is between 40 and 60 neurons, where the results are optimal, and that adding any number of cells will have no effect on improving model performance and will cause oscillations that may lead to overfitting or oversensitivity.

Based on the previous experiment that relied on a large number of neurons (150 neurons), the results showed that 40 neurons may be sufficient to produce the best results. Considering reducing the number of neurons to avoid model complexity and reduce time calculations, we will analyse the coefficient of determination (R^2) and mean square error (MSE) curves.

a_performance:

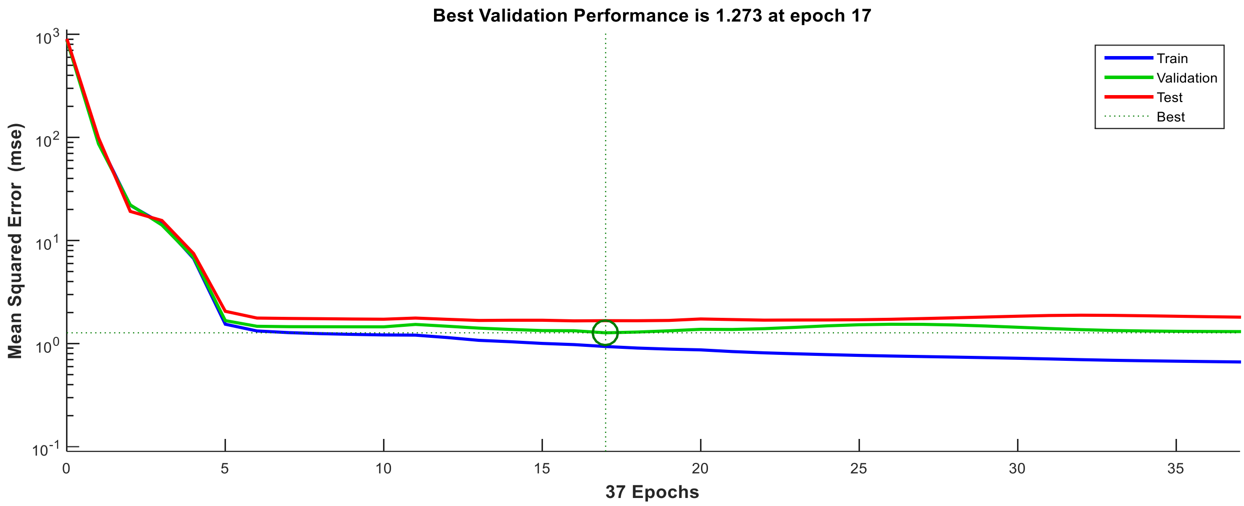


Figure III.6: MSE Variation with Number of Epochs

The graph represents the relationship between the number of loops and the mean square error (MSE) for training, verification and testing where we observe that the error decreases sharply in the first loop (from 0 to 5 loops) which indicates the speed of learning and then continues to improve gradually until it reaches the best verification performance at 17 epoch with an MSE value of 1.273, after that the verification error starts to rise slightly which indicates the start of overfitting .

Conclusion:

The model shows good performance and it is preferred to adopt the model at Epoch 17 with MSE = 1.273. It achieves the best performance and balance between accuracy and generalisation. To avoid overgeneralisation (overfitting), training will continue to be optimised at the expense of verification and the balance will be disturbed .

B_The Regression:

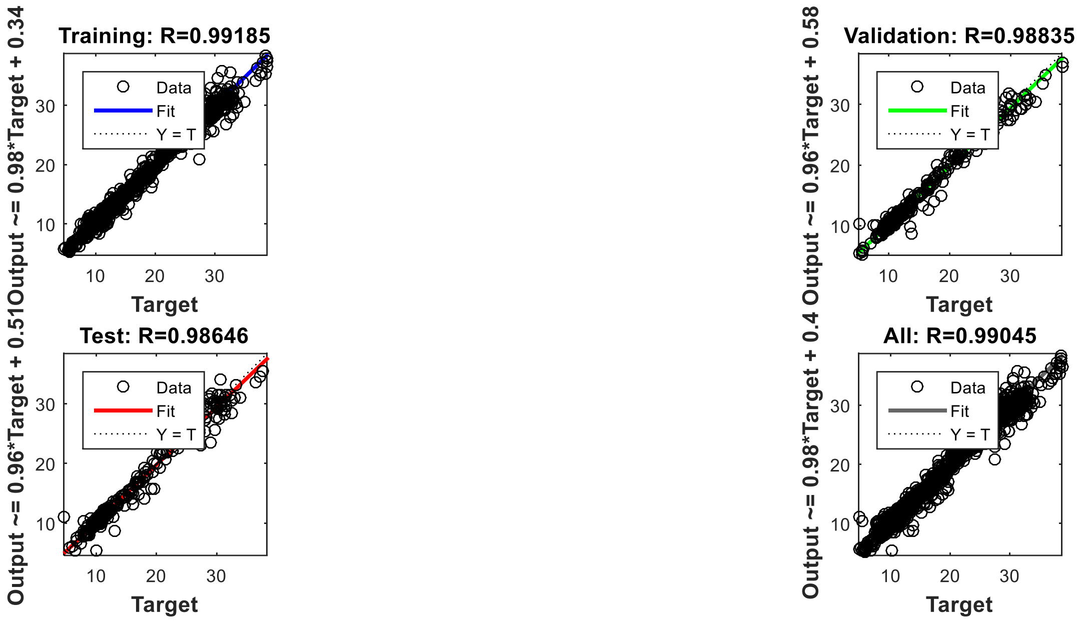


Figure III.7: The Regression Variation with Target

Analyze the results

The four graphs represent analytical plots .The performance of a neural network in predicting Target values based on the output results during the training, validation, testing, and total (All) data is measured using the correlation coefficient R. Curve analysis.

Training:

The graph represents the linear relationship between the predictive model and the training data, where we observe that the data points are spread along the predictive model line in a balanced manner. The correlation coefficient (R) indicates a strong correlation of 0.99185, indicating the model's ability to predict the values with high accuracy.

Conclusion: The model showed accurate learning of the relationship between the data and no clear indication of poor learning.

Validation:

The graph represents the linear relationship between the predictive model and the validation data, where we observe that the validation data points are well spread along the predictive model line and the correlation coefficient is high (0.98835), indicating that the model generalises well to data that was not used during training.

Conclusion: The model shows the ability to recognise new data and there is no indication of overfitting

Test:

The graph represents the linear relationship between the predictive model and the test data, where we observe that the test data points are well spread along the predictive model line and the correlation coefficient is high (0.98646), indicating that the model performs excellently even on unseen data during training.

Conclusion: The model shows stable performance with diverse data that was not used in the training or validation period.

All Data :

The graph represents the total performance for all data (training + validation + testing), where we observe that the data points are spread along the predictive model line in a compact and excellent manner as shown by the correlation coefficient (0.99045), indicating that the model is balanced and accurate in predicting across all parts of the data.

Conclusion: The model showed flexibility and a good ability to balance between accuracy and generalisability.

Total Result

The results show that the model achieves a very high agreement between the predicted values and the target with a correlation coefficient of 0.99185 for training, 0.98835 for verification, and 0.98646 for testing, with an overall correlation coefficient of 0.99045 for all data indicating that the trained network predicts accurate results, which confirms the efficiency of the model in learning and generalisation without indications of over-learning .

The following curve shows the results obtained based on the comparison with the real values :

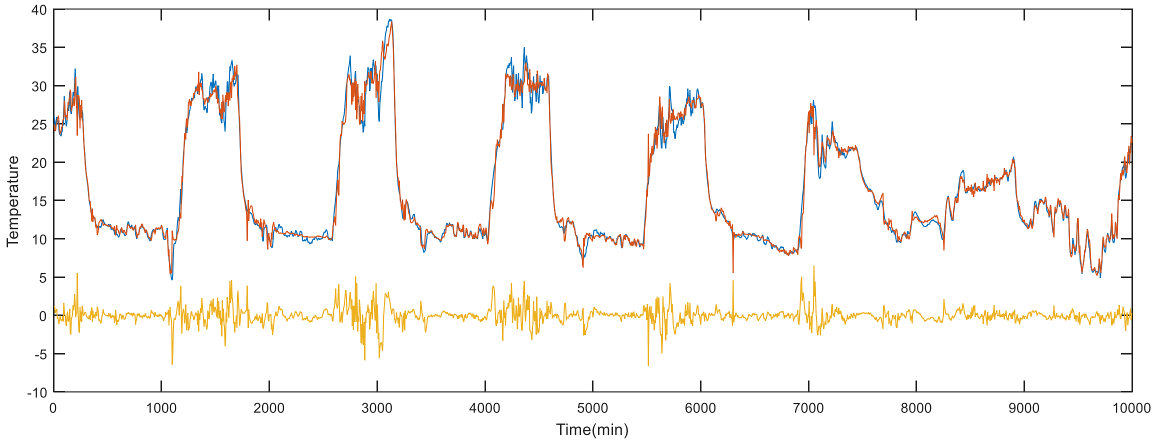


Figure III.8: Comparison of real and predicted temperature values

This graph compares real and predicted temperatures over a time span of 10,000 minutes. The curve shows a good match in most periods, reflecting the model's ability to recognise the temporal pattern of temperature changes accurately. Although there are some periods where there is a small difference between the real and predicted values, this is normal due to the sudden and rapid changes in the data.

Conclusion: The results show a very good performance in the model's ability to deal with temporal dynamics.

III.5.2. Cascade-forward backprop

a_The Pearson R^2:

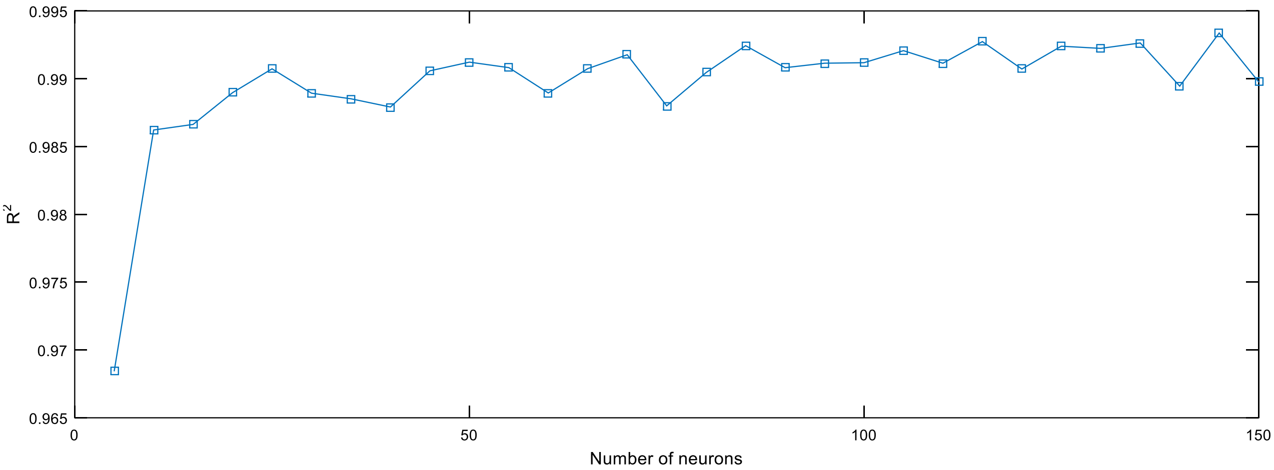


Figure III.9: The effect of the number of neurons on the model performance index R^2

The graph represents the relationship between the number of cells and the performance of the model measured using the coefficient of determination R^2, where we observe a rapid development in the performance of the model up to more than 0.985 under the use of only 5 to 10 neurons, then the pace of increase slows down until it reaches 25 neurons, where the peak performance of the model is about more than 0.99, indicating the saturation of the model, when the number of cells exceeds 25 cells, we notice fluctuations in the performance of the model as a result of over-fitting or over-sensitivity.

b_MSE:

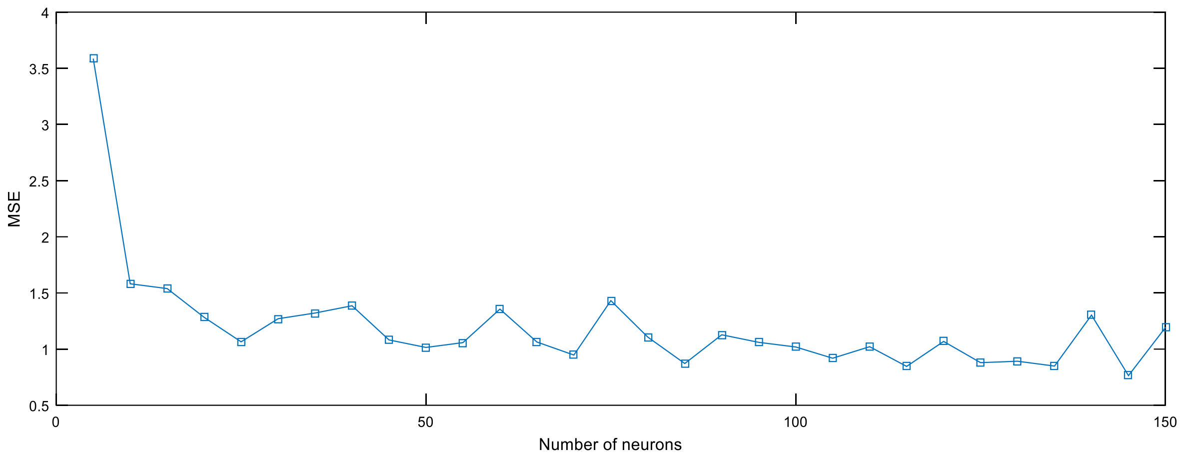


Figure III.10: Effect of Neuron Count on Mean Squared Error (MSE)

The graph represents the relationship between the number of cells and the error rates of the model, where we observe that the error rates peak around 4.5 and then start decreasing sharply when the number of cells exceeds only 10 neurons with a value of 1.5MSE and then continues to decrease at a slow pace with oscillation until it reaches 25 neurons with a value of 1 MSE. When the number of neurons exceeds 25, the curve continues to oscillate and approaches a value of about 1.5 and 0.3

Results:

When analysing the two curves $R^2$and MSE, , we find that the best value for model performance is 25 neurons, where the results are optimal with a value of 0.99 and a performance error of less than 1 MSE, and that adding any number of cells leads to instability in model performance, and will cause oscillations with large differences due to overfitting or over-sensitivity.

Based on the previous experiment with a large number of neurons (150 neurons), the results showed that 25 cells represent the best performance result from the model, we will analyze the coefficient of determination (R^2) and mean square error (MSE) curves.

a_performance:

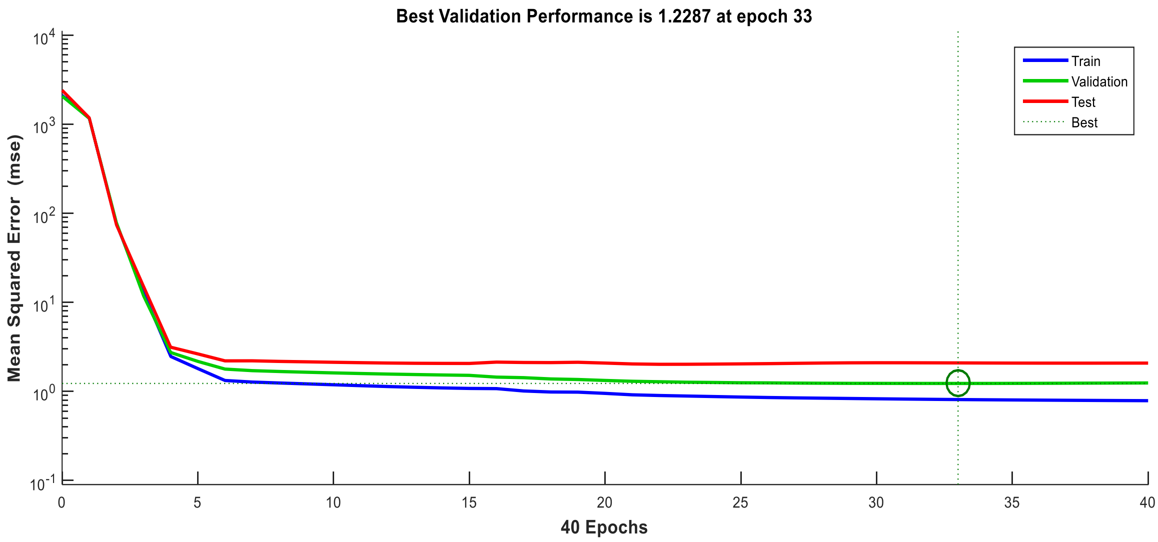


Figure III.11: MSE Variation with Number of Epochs

The graph represents the relationship between the number of loops and the mean square error (MSE) for training, verification and testing, where we observe that the error decreases sharply and smoothly from 0 to 5 loops, which indicates the speed of learning and then continues to improve gradually until it reaches the best verification performance at 33 loops with an MSE value of 1.2287.

It is preferable to adopt the model at epoch 33 as it achieves the best performance and balance between accuracy and generalisation. To avoid overgeneralisation (overfitting) .

B_The Regression:

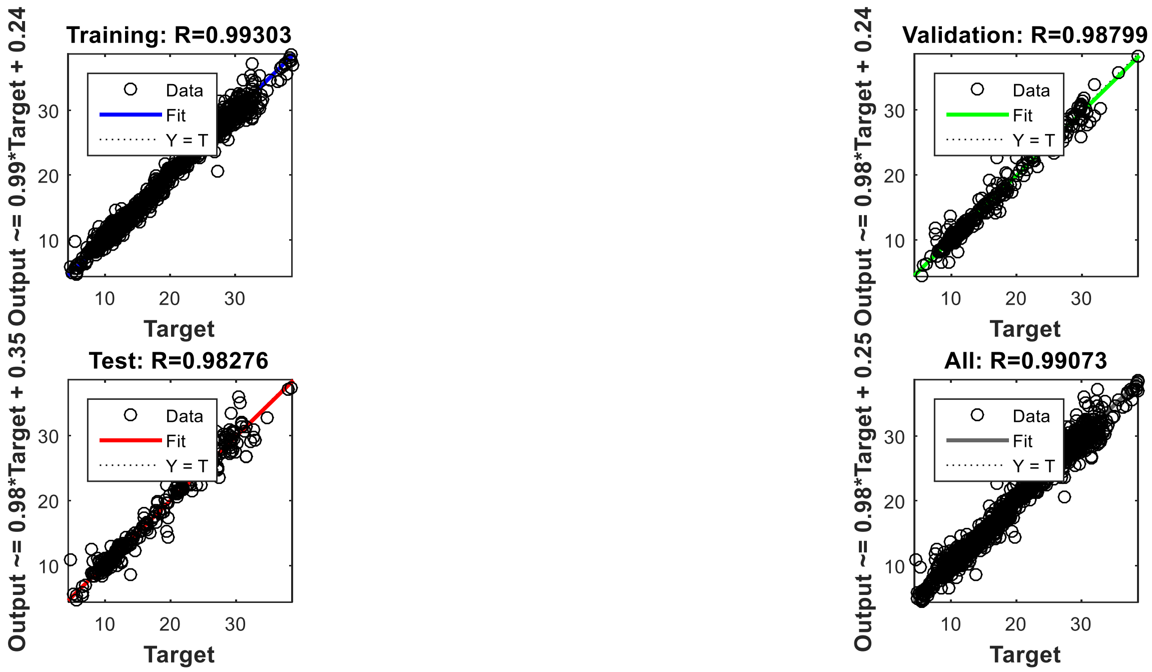


Figure III.12: The Regression Variation with Target

Analyze the results

The four graphs represent analytical plots .The performance of a neural network in predicting Target values based on the output results during the training, validation, testing, and total (All) data is measured using the correlation coefficient R. Curve analysis:

Training:

The graph represents the linear relationship between the predictive model and the training data, where we observe that the data points are spread along the predictive model line in an excellent manner with a correlation coefficient value of 0.99303, indicating an excellent agreement between the predictions and the actual data.

Conclusion: The learning process during internships is well facilitated and the model does not suffer from underfitting.

Validation:

The graph represents the linear relationship between the predictive model and the validation data, where we observe that the data points are spread along the predictive model line in a good way, but slightly less than the training, with a correlation coefficient value of 0.98799

There is also no dispersion in the data around the linear model, indicating no overfitting

I appreciated the interaction of the model and generalisation when verifying new data.

Test:

The graph represents the linear relationship between the predictive model and the test data, where we observe that the data points are spread along the predictive model line in an excellent manner with a correlation coefficient value of 0.98276, indicating an accurate prediction of the data.

Conclusion: The model achieved reliable and consistent performance in the prediction process after using completely new and previously unlearned data.

All Data :

The graph represents the linear relationship between the predictive model and the training data, where we observe that the data points are spread along the predictive model line in a compact and dense manner, confirming that the model deals efficiently with all the data, and has a high correlation coefficient value of 0.99073.

Conclusion: The model performed excellently and had a good balance between training and generalisation.

Result Total

The model showed excellent performance with all types of data, especially new and unprecedented data, and $R > 0.98$ indicates the validity and robustness of the model and supports the presence of dispersion around the target line to a small percentage, indicating that there is no overfitting or underfitting.

The following curve shows the results obtained based on the comparison with the real values :

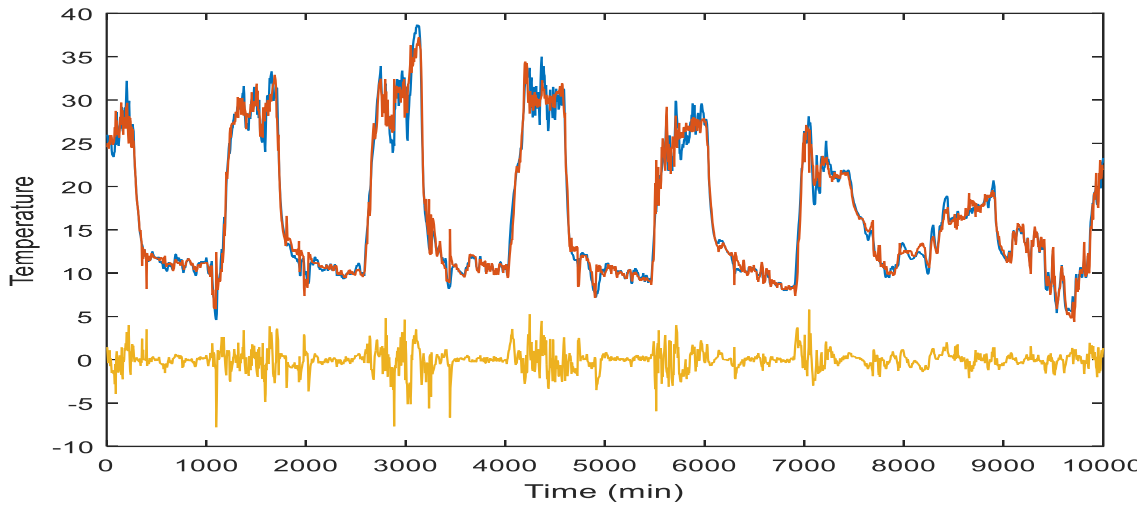


Figure III.13: Comparison of real and predicted temperature values

The graph shows a comparison between the actual and predicted temperatures over a time period of 10,000 minutes. The model shows an accurate performance in tracking the temporal behaviour of temperatures, with a high agreement between the actual and predicted values in most periods, demonstrating the model's efficiency in learning and prediction. The slight discrepancies that appear in some places are expected and are mostly due to sudden and rapid changes in the thermal data.

Conclusion: The results show a very good performance in the model's ability to deal with temporal dynamics.

III.5.3 Comparison of Feed-forward backpropagation and Cascade-forward backpropagation results:

The Standard	Feed-forward backprop	Cascade-forward backprop
Accuracy	Good, but slightly inferior to Cascade	Highest accuracy in output prediction
MSE	Slightly higher	Less, indicating better performance
Training Time	Faster	Relatively slower due to the more complex structure
Number of nodes and layers	Less	More, including additional connections from previous layers
Prediction	Good, especially with similar data for training	Better at prediction even with unseen data
Stability	Stable performance in most cases	More stable and less volatile results
Convergence	Sometimes fewer epochs are required	Needs a larger number for optimal performance
Ease of tuning	Easier to choose transactions	Relatively harder due to the complexity of the structure
Generalization	Good	Excellent, especially in complex cases
Visualization	Error curve gradually decreases	Error curve decreases faster and more stable

Tab1:Comparison of Feedand Cascade

III.6.Convolutional Neural Network:

III.6.1.Settings for training

The VGG-16 convolutional neural network model was used to train the temperature prediction data. The following parameters were used in the training process: A training cycle of 20 epochs and 30 iterations was used for a total of 600 iterations while maintaining a constant learning rate of 1 CPU.

III.6.2 Forecasting results using the VGG-16 model

a. **MRSE Analysis :**

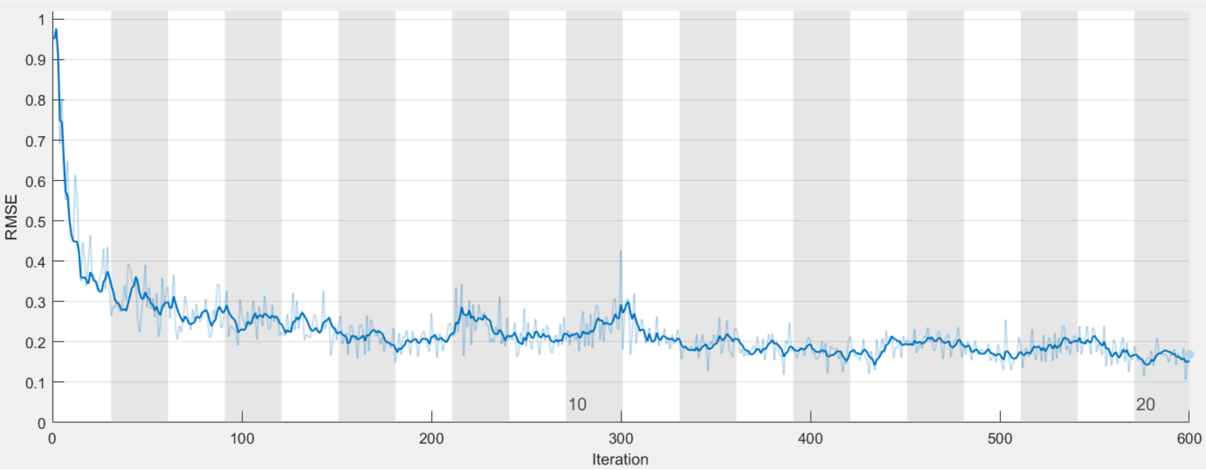


Figure III.14:MRSE Variation with Number of Iteration

The graph represents the relationship between the number of iterations and the mean squared error (MSE), where we observe that the error is high close to 1 and then drops sharply during the first 50 iterations, after which it continues to gradually improve and shows some fluctuation until it stabilises at a value between approximately 0.2 and 0.3 after iteration 100, indicating a gradual improvement in performance as the prediction becomes more accurate with each additional iteration.

b. LOSS Analysis :

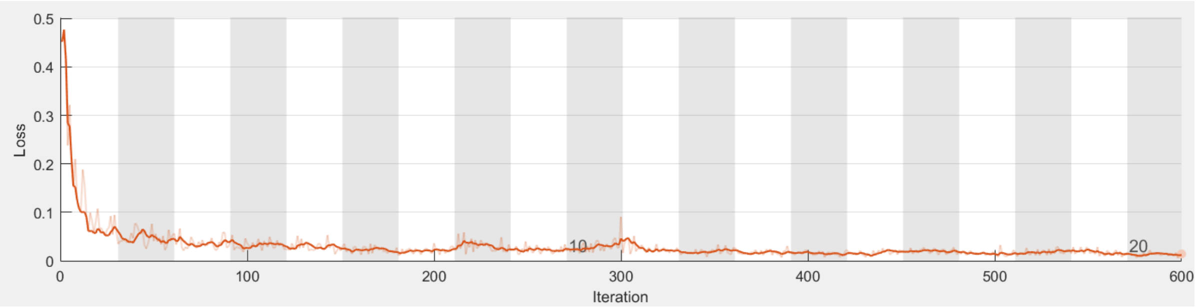


Figure III.15: LOSS Variation with Number of Iteration

The graph represents the relationship between the number of iterations and the model loss, where we observe that the model loss is high near 0.5 and then drops sharply during the first 50 iterations, after which it continues to gradually improve until it stabilises at a value close to 0.02 after 300 iterations with very slight oscillations, which indicates that the model learns from the data effectively and stably.

Conclusion: High performance results show that the model learned well and showed no indication of overfitting based on the lack of significant oscillation and low level of error, indicating acceptable prediction accuracy.

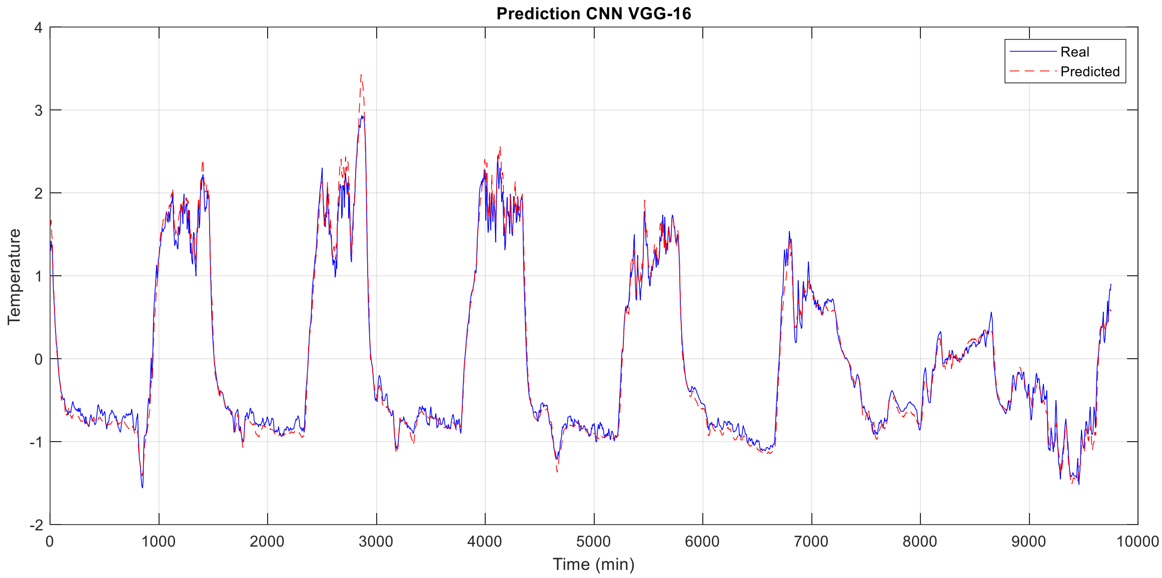


Figure III.16: Comparison of real and predicted temperature values

The following curve shows the results obtained based on the comparison with the real values :

The graph represents a comparison between the real temperature values and the predicted temperatures over a time period of 10,000 minutes, where we observe a good match in most periods, which indicates the success of the model in capturing the temporal pattern of temperature changes, we also observe a mismatch in some periods, but this is normal due to the rapid changes.

Conclusion: The results show a very good performance in the model's ability to deal with temporal dynamics, showing a high tracking ability in temperature rise and fall over time.

III.7 Comparative Performance Analysis of Neural Network Models in EAHE Temperature Prediction:

In this table, we have evaluated the models obtained to predict EAHE performance and highlighted which model is the most effective

Model	Best MSE	Best R^2	Training Time (min)	Stability
Feed-forward Backpropagation	0.80	0.993	30	Medium
Cascade-forward Backpropagation	0.50	0.995	40	Medium
CNN VGG48	0.00*	1.00*	10,000	Extreme

Tab2:Comparison of Feed and Cascade and CNN

Comparison result

The Convolutional Neural Network (CNN) has outperformed artificial neural networks due to its ability to naturally and smoothly handle time series, automatically extract features, and minimise the number of coefficients, enabling us to accurately model the output of geothermal heat exchangers

III.8 Conclusion

This chapter is a pivotal point where we present and analyse the results obtained using two types of artificial neural networks (Feedforward and Cascade-forward) and convolutional neurons in MATLAB environment to build an accurate predictive model for the output of geothermal heat exchangers, we were able to create three different structural models.

The results in terms of artificial neural networks showed a convergence of performance between the two models in terms of accuracy, learning speed and output prediction, but the feed-forward network represented the best results and the highest accuracy in predicting the thermal values, which proves its efficiency in dealing with non-linear characteristics. As for convolutional neural networks, they achieved good and stable performance in terms of prediction, which made them more effective .

General Conclusion

General Conclusion

The EAHE is a viable alternative to conventional chillers in the desert environment as it has proven to be effective in climate variability throughout the year while ensuring thermal comfort in homes and saving energy consumption, and this work demonstrates the application of artificial intelligence (AI) capabilities to enhance the understanding of this system. We could model the output of the EAHE based on deep learning, thereby reducing the costs of field experiments and improving the system's performance.

This experimental work is an important step in demonstrating the ability of deep learning to develop predictive models and exploit them in the development of thermal and renewable energy. Although the study achieved its objectives, there are some limitations, such as the inability of the models to generalise beyond the training data, the need to provide large datasets to achieve more accurate performance, and the use of optimisation techniques such as hyperparameter tuning and regularisation to build an augmented model.

In summary, this study has demonstrated the effective role of neural networks in optimising the performance of geothermal heat exchanger systems, facilitating a path towards sustainable development in the field of energy and environmental engineering

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الجمـهورية الجزائرية الـديمقراطية الشعبية
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Université Ghardaïa
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شهادة ترخيص بالتصحيح والايداع:

انا الاستاذ(ة) موسى اسامة
بصفتي المشرف المسؤول عن تصحيح مذكرة تخرج (ليسانس/ماستر/دكتورا) المعنونة

بـ:

Modeling of Geothermal EAHE Outputs Using

Convolutional

Neural Network and Artificial Neural Network in Ghardaia

من انجاز الطالب (الطلبة):

بوعامر شيماء

التي نوقشت بتاريخ : **11-06-2025**

اشهد ان الطالب/الطلبة قد قام /قاموا بالتعديلات والتصحيحات المطلوبة من طرف لجنة المناقشة وقد تم التحقق من ذلك من طرفنا وقد استوفت جميع الشروط المطلوبة.

رئيس قسم الآلية والكهروميكانيك
عزاوي محـــمد

امضاء المسؤول عن التصحيح
مصادقة رئيس القسم