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# Artificial Intelligence Network Approaches for Image Classification in Sudan

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***Abstract*****—** *The article highlighted the objective of crop classification using Artificial Intelligence Network approaches for Image Classification in Sudan to enhance the appropriate conditions for knowing the types of crops and the optimal use of arable lands to estimate the quantity and quality of crops, and to assess the ability to control the food security and economically efficient situation, which also includes increasing the benefits and reducing the risks of misclassification of crops, which in turn leads to the lack of knowledge of food stocks and the occurrence of famines. The research aims to use modern Artificial Intelligence techniques for classifying crops and designing a model that supports the correct classification to reduce the time, effort, and costs of crop classification. The methodology relied on two main phases: the analysis phase and the planning and design phase. In the analysis stage, the problem tree and the vision the tree was created, and the strategies for possible solutions by using free Sentinel-2 remote sensing satellite images. The planning and design stage consisted of developing the framework design to reach the pre-determined goal by the agreed strategy, and to prepare the schedule and maps for the selected study area. The classification was implemented through monitoring and evaluation of the methods used in the cop classification*.

***Keywords*****—** *AI: Artificial Intelligence, Neural Network, OBIA: Object-based image analysis, Random Forest Model*.

## I. INTRODUCTION

In this study, remote sensing was utilized to collect precise and sufficient data for detailed analysis of the natural and topographic characteristics of the Earth's surface in the areas under investigation. The raw data from remote sensing images was processed using optimal techniques and programs to achieve satisfactory results. One of the most advanced techniques used is Artificial Intelligence (AI), which has demonstrated its effectiveness and success in providing geospatial data, recognizing features, and classifying images. This technology is highly effective in identifying remote sensing images, as well as identifying and classifying crops.

In Sudan, agriculture is the main source of food and "the cornerstone of the economic development of the country". The study aims to analyze and classify satellite images to know the cultivated areas, identify and classify crops; and maintain sustainable food production. The diversity of agricultural resources requires continuous monitoring and development for producers and farmers (Figure 1) to advance investment and management programs further. Sudan is one of the countries with vast agricultural areas, multiple irrigation methods, and climatic diversity. This provides the possibility to grow different types of crops. However, these techniques are not being fully utilized due to the limited application of AI, high-resolution remote sensing images, and GIS technology in agricultural operations. The paper highlighted the implementation of AI Neural Networks for image classification to identify the cultivated crops with the required achievable accuracy and comprehensiveness.

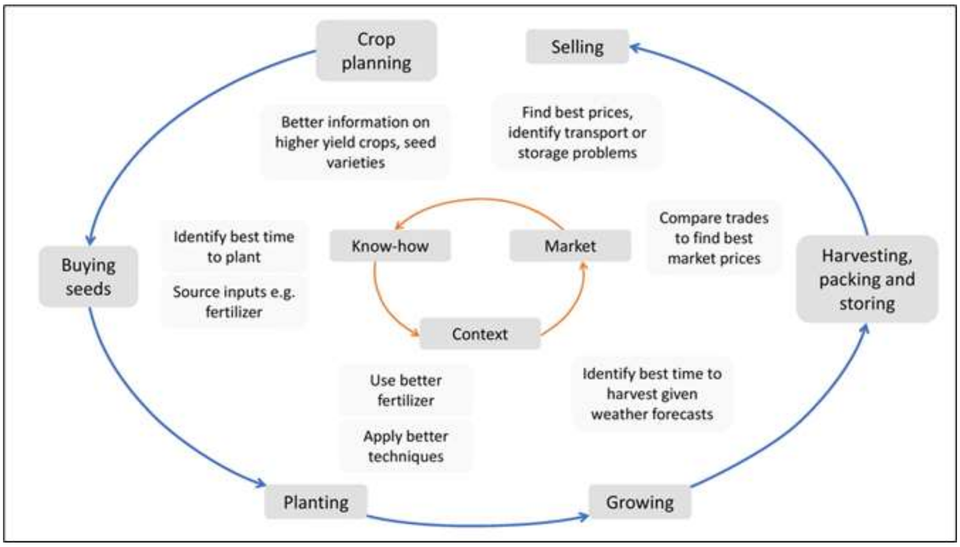

Figure 1. Equipment, methods, and information needed for the farmers [1]

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Sudan has a unique location that links the Arab world in Northern Africa to Africa south of the Sahara; with the geographic coordinates Latitudes of about 8° and 22° North and longitudes of 22° and 38° East[2]. Agriculture is the backbone of Sudan's economy, with a diverse and disparate range of climates and fertile lands, making it the world's food basket due to its water resources and land. Sudan has a tropical sub-continental environment, ranging from a desert environment in the north to a belt of summer rain contributes to a semi-arid climate. Unfortunately, little attention has been paid to developing and implementing well-known international best practices in Sudan.

Figure 2. Sudan Location

Agriculture in Sudan relies mainly on rainfall and irrigation from the Nile River and its tributaries. the country has a diverse range of agricultural zones and crops, and there are various ways to classify crops based on their intended use, type, and cropping methods. the primary techniques, for classifying crops include conventional agricultural methods, classical methods using satellite data, and modern techniques that utilize artificial intelligence and satellite imagery analysis. advanced technologies such as remote sensing and geographic information systems are employed for crop classification using satellite images. these methods can be implemented to classify crops based on economic factors, cultivated areas, seasonal crops, and specific purposes.

## II. Images Classification

Many image classification methods have been developed and widely used to generate classified data [3]. In remote sensing image processing, the primary classification procedures are supervised classification, unsupervised classification, and object-based image classification. The supervised classification procedure is usually used when the Classifier has in-depth expertise in an area of interest; the idea behind supervised classification is that the Classifier selects sample pixels from an image representing a class in the image and instructs the software to use these training pixels to categorize all other pixels in the image; The training site is selected based on the user's knowledge [4], the classifiers select representative samples from each land cover class of the supervised classification. There are numerous algorithms used for supervised classifications for example: Maximum likelihood; Distance; Principal components; Support vector machine (SVM); and Iso cluster. Training data can be chosen depending on some considerations such as Visits to the site, Data with high spatial resolution, old data, and earlier maps. An example of the expertise of the investigator in the Supervised Classification is illustrated in (Figure 3), possible training sites for agriculture, water, and urban land cover types are represented in [5], the simple steps for conducting classification are Selecting training areas, Generating a signature file, and Classifying.

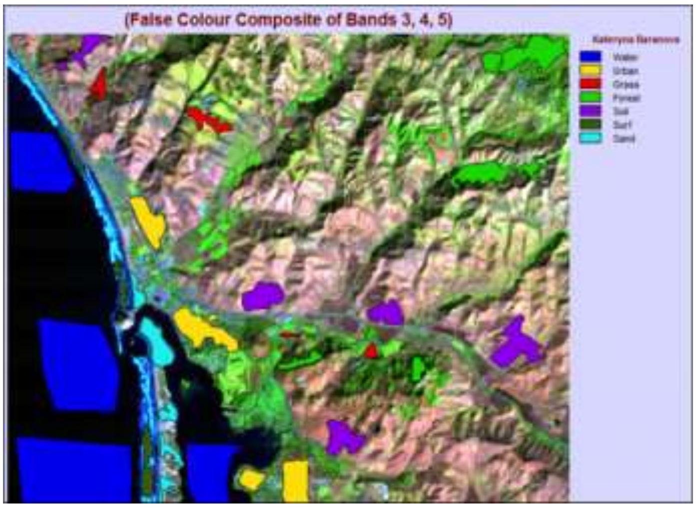

Figure 3. Supervised Classification

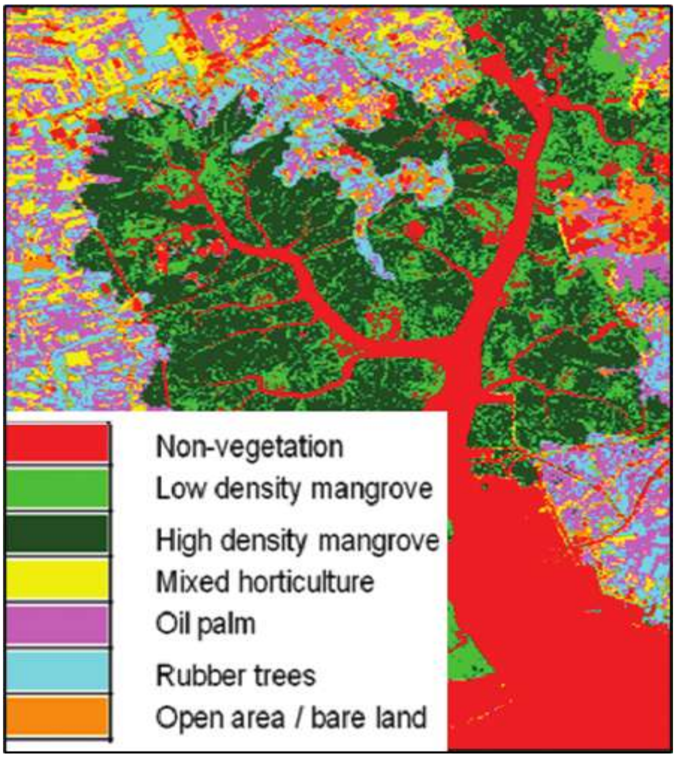

Figure 4. Unsupervised classification

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The unsupervised image classification method (Figure 4), uses software to classify many unknown pixels in an image according to their reflectance values, it groups pixels into “clusters” based on their properties [4] without the analyst's intervention, and no need for samples for classification, as it’s an easy way to segment and understand an image. The most common clustering approaches for unsupervised classification are K-means and Iterative Self-Organizing Data Analysis Technique (ISODATA)[4]. Common steps to conduct unsupervised classification: Generate clusters and assign classes.

Both supervised and unsupervised classifications used Pixel-based classification; it generates square pixels, with each pixel having a unique class. However, object-based picture classification divides pixels into representational vector shapes with size and geometry.

Object-based image analysis (OBIA) is one of the numerous methodologies designed to overcome the limitations of pixel-based approaches. It uses spectral, textural, and contextual information to determine thematic classes in an image[4], Each object (segment) is classified in the following stage based on one or more statistical properties of the pixels present. It means that all pixels inside a segment are allocated to a single class, addressing the difficulties associated with pixel-based techniques such as within-field spectral variability and mixed pixels. Several investigations have proven OBIA's superiority over pixel-based classifications, particularly in varied agricultural landscapes and urban regions[4], by grouping pixels, object-based image analysis (OBIA) segments an image (Figure 5) [7].

Figure 5. Object-based image analysis (OBIA)

*Segmentation*

Segmentation is the key to classification, it divides the image into objects that represent features of the ground, and classification classifies objects according to their shape, size, spatial and spectral characteristics. The steps followed to perform object-based image analysis classification are shown in (Figure 6)[7].

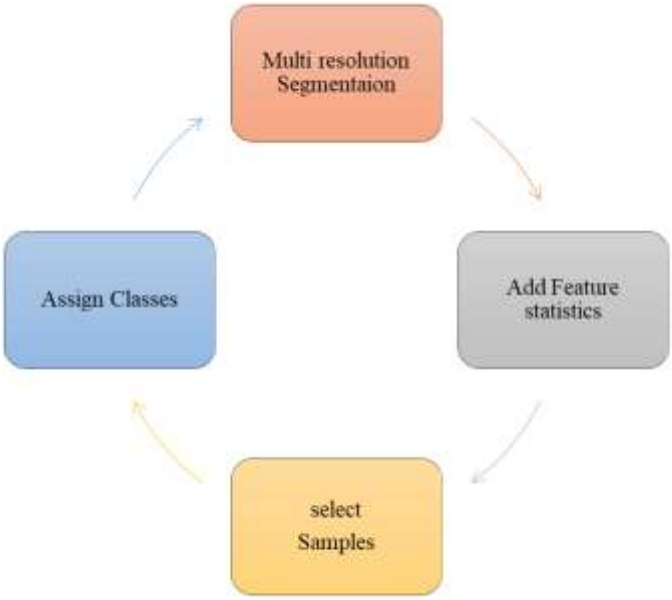


Figure 6. Steps to perform object-based image analysis classification

TABLE 1. Summary of Remote Sensing Classification Techniques[8]

| Method | Examples | Characteristics |
|---|---|---|
| **Parametric** | Maximum Likelihood classification. Unsupervised classification. | Assumptions Data area, normally distributed Prior Knowledge of class density functions |
| **Non-Parametric** | Nearest-neighbor, Fuzzy Neural networks support vector machines | No prior assumptions are made |
| **Non-metric** | Rule-based Decision tree classification | Can operate on both real-valued data and nominal scaled data statistical analysis |
| **Hard (parametric)** | Supervised and Unsupervised | Classification using discrete categories |
| **Soft (non-parametric)** | Fuzzy Set Classification logic | Considering the heterogeneous nature of the real world, each pixel is assigned a proportion of the in-land the cover type found within the pixel |
| **Pre-Pixel** | | Classification of the image pixel by pixel |

## III. COMMON IMAGE CLASSIFICATION PROCEDURES

The common image classification procedures consisted of creating an image classification scheme; performing field surveys in the research region to gather ground information and other auxiliary data; image pre-processing including radiometric, atmospheric, geometric, topographic corrections, enhancement, and preliminary image clustering; selecting sample sections of the image and assessing the initial clustering findings or generate training signatures, using the image classification algorithms; post-processing that includes extensive geometric rectification and filtering and classification results that are compared to field studies to determine the accuracy[8] of the raster data (Figure 7)[9].

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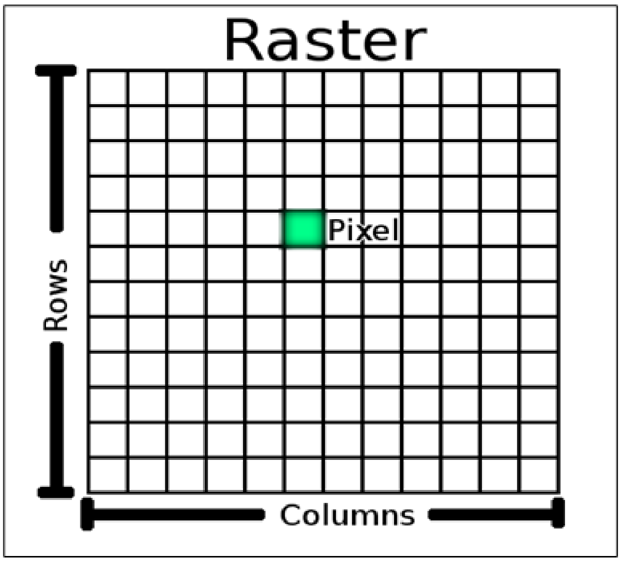

Figure 7. Raster Data structure

## IV. Remote Sensing in Agriculture

Many federal and state ministries in Sudan commission their personnel to map crop types, for agriculture and food security every year. However, the agricultural surveys are too expensive to cover all areas in Sudan, so they only cover a portion of farms [10]. Remote sensing data and supplementary information together allow the determination of crop spatial distribution at various spatial scales with relatively minimal financial investment [10], knowing that certain crops are spectrally similar, where pixel sizes can sometimes impact crop acreage estimates, resulting in varying inaccuracies [10]. From a vantage point high above a field, remote sensing images from satellites, photogrammetry, Lidar, and UAV allow for an analysis of agricultural conditions remotely.

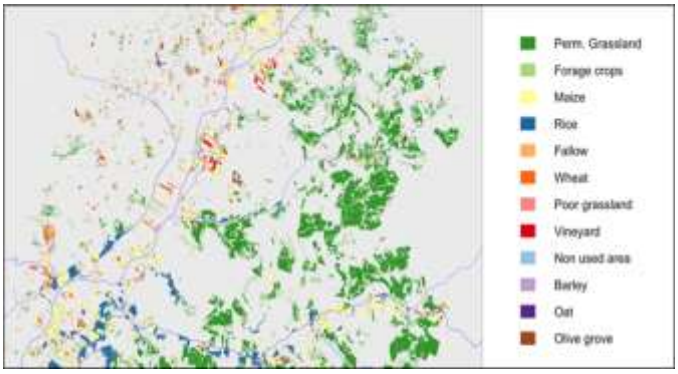

Figure 8. Agricultural parcels automatically identified

Many remote sensing techniques are used in agriculture, but the most common is the passive system, which detects electromagnetic radiation reflected from plants. Passive systems are powered by the sun; sensors for passive systems can be placed on satellites, manned or unmanned aircraft, or directly on farm equipment. When selecting a remote sensing system for a certain application, numerous parameters must be considered, such as spatial resolution, spectral resolution, radiometric resolution, and temporal resolution[11].

## V. Differences in Resolution of Images

*Spatial resolution*

A spatial resolution refers to the size of the pixel, which is the smallest component or object that can be recognized in an image. As the size of a pixel decreases, the image's resolution increases. For example, an image with a spatial resolution of one meter corresponds to an area of one square meter.

Figure 9. Images spatial Resolution

*Spectral resolution*

A band is a limited section of the electromagnetic spectrum, in which the number of bands and the wavelength width of each band are referred to as spectral resolution. In images with increased spectral resolution, shorter wavelengths can be detected. Multi-spectral photography may measure a variety of wavelength bands, such as visible green and near-infrared (NIR). Hyperspectral imagery detects energy in narrower and many bands than multi-spectral imagery. The narrow bands of hyperspectral photography are more sensitive to fluctuations in energy wavelengths and hence have a greater potential to identify crop stress than multi-spectral data.

*Radiometric resolution*

A remote sensor with a high radiometric resolution can distinguish small differences in reflectance values more easily. A sensor with a higher radiometric resolution can better view a specific part of the electromagnetic spectrum.

*Temporal resolution*

Temporal resolution measures the number of remote sensing platforms that can cover a given area. Unlike geostationary satellites, which can provide continuous sensing, conventional orbiting satellites can only provide data while passing over an area. Sensors mounted on planes are often used to collect data for more frequent sensing applications requiring remote sensing. Cloud cover can prevent data in a planned remote monitoring information system.

## VI. GIS and Remote Sensing Integration

GIS is used to create maps, but it is also used to store and use satellite-linked spatial systems; foresters and farmers could use spatial information systems to monitor their standing crops; natural resource management advancements and environmental management methods could be compared with the integration of satellite data while processing findings [12]. Images obtained from optical and digital remote sensing equipment mounted on

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aircraft and satellites provide a substantial amount of geographical information and data for GIS input. Remote sensing data are valuable information for mapping natural resources such as geology, forestry, water resources, land use, and land cover. The combination of the two technologies, remote sensing, and GIS can be utilized to create decision-assistance planners or decision decisionmakers systems. Remotely sensed images can be used as a source of geospatial data in GIS and for analyzing remotely sensed data in pictorial and digital modes [12]. As a result, remote sensing has developed as a powerful source of spatial data as an input for GIS in recent years, allowing a detailed map to be produced with the help of other collateral data obtained from a range of different sources[12].

## VII. Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science that focuses on constructing machines that can engage in behaviors that humans deem intelligent. Humans have been fascinated by the ability to make intelligent machines since ancient times; nowadays with the introduction of the computer and AI programming techniques, the dream of intelligent machines is becoming a reality. Researchers are developing technologies capable of simulating the human mind. Artificial neural networks (ANNs), which are informed by the structure of the brain, are the key to making computers more biological and assisting machines in reasoning like people [13], Artificial intelligence is defined by the creation of machines that think. The term "artificial intelligence" refers to a synthesis of computer science, physiology, and philosophy. Machine vision to expert systems is just some examples of the many topics within AI [14]. The most challenging technique in artificial intelligence is to replicate the behavior of the human brain, which is made up of billions of neurons and is one of the most complex substances in the universe.

## VIII. Neural Networks

The term Neural originates from the human nervous system's basic functional unit neuron or nerve cells present in the brain and other parts of the human body. A Neural network is a group of algorithms that certify the underlying relationship in a data set similar to the human brain. The neural network helps to change the input so that the grid gives the best result without redesigning the output procedure[15]. Neural networks (Figure 10), which are known to imitate or simulate the activity of the human brain to solve complex data-driven issues, are the functional units of Deep Learning. The input information is processed layer by layer to obtain the desired result by different layers of artificial neurons, and neural networks have been used in various fields [16], such that: -

The Biological Neuron (a): The nerve cell, often known as a neuron, is the basic computational unit of the neurological system[17].

The Artificial Neuron (b): The purpose of artificial neural networks is not the reproduction of the brain. On the contrary, used to understand nature's capabilities to create answers to challenges and simulate the four essential functions of real neurons[18]: Sensory information

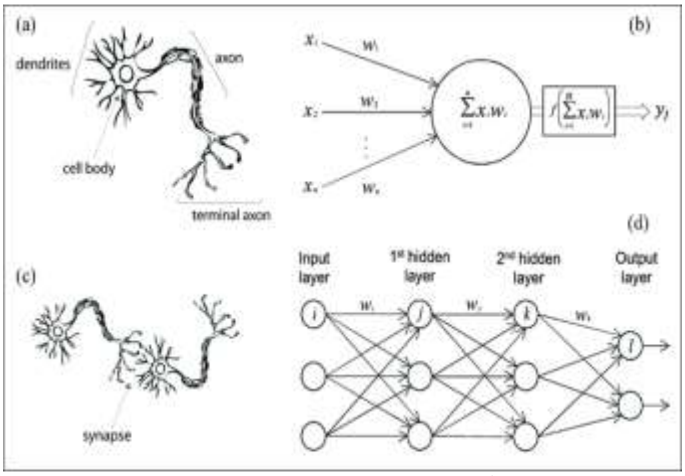


Figure 10. A biological neuron in comparison to an artificial neural network

reception; perception of unique sensations, sensation integration; and reaction creation. The basic unit of the artificial neural network is shown in (Figure 10) depicts a basic model of an artificial neuron. In general, artificial neurons are divided into three types, these are the McCulloch and Pitts Model, the Perception Model, and the ADALINE Model[18].

## IX. The Structure of Artificial Neural Network

The Artificial Neural Network design (Table 2) is made up of discrete components called neurons that imitate the brain's biological functioning [19]. The several parts of the Artificial neuron are shown in (Figure 11) [20]. In general, neural networks are divided into two types: supervised networks and unsupervised networks. The ability of the training algorithm determines how the network architecture is developed. The design of the corresponding training algorithm is deemed vital in the majority of newly suggested network topologies.

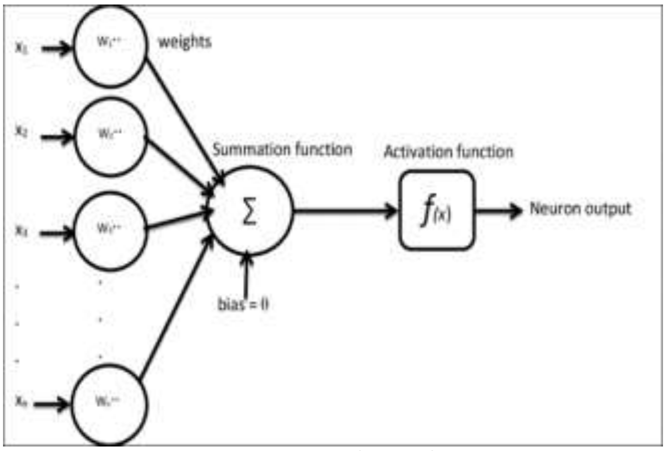


Figure 11. The structure of the artificial neuron

There are several distinctions, in which, artificial neurons often imitate only one component of biological neurons, integrating and firing with nonlinearity (Figure 12) [17]. Real neurons use neural spikes rather than real-valued outputs, and messaging is probabilistic because the neurotransmitter may or may not be absorbed by the post-synaptic neuron. There are also other differences. Artificial networks attempt to duplicate as

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many of the properties of biological neurons as possible; however, they are generally used to solve scientific challenges in neuroscience rather than machine learning difficulties; some of these differences are shown in (TABLE 3)

TABLE 2. Common Components of Neural Network

| Factor | Function |
|---|---|
| Input (X) | Input is features fed into the model during the learning process. For example, in object detection, the input can be an array of pixel values from an image; the data that feeds into the model comes from external sources such as a CSV file or a web service, loaded into the input layer. It is the only visible layer in the Neural Network design that passes all data from the outside world without processing. |
| Weight (w) | The primary job is to prioritize features that contribute the most to learning. It accomplishes this by employing scalar multiplication between the input value and the weight matrix. A negative word, for example, would have a more significant impact on the sentiment analysis model's judgment than two neutral terms. |
| Bias | The bias is responsible for adjusting the value produced by the activation function, similar to how a constant works in a linear function. A layer is created when multiple neurons are arranged in a sequence, and a multi-layer neural network is formed when several layers are stacked next to each other. |
| Activation Function | It brings non-linearity into perceptron operation to account for variable linearity with inputs. Without this, the output would be a linear mixture of the input values, and the network would be incapable of introducing non-linearity |
| Hidden Layers | A hidden layer in (Figure 10) is placed between the algorithm's input and output in neural networks, where the function assigns weights to the inputs and guides them through an activation function as the output. In short, the hidden layers conduct nonlinear modifications on the network's inputs. Hidden layers change according to the function of the neural network, and the layers may also vary according to their associated weights[21]. Biological neurons receive input signals from other neurons through dendrites and send out output signals by axons that radiate outward and connect to other neurons. The input signal is represented by (x) in (Figure 11), and when it 'Moves,' it is multiplied (w x) based on the weight variable (w). |

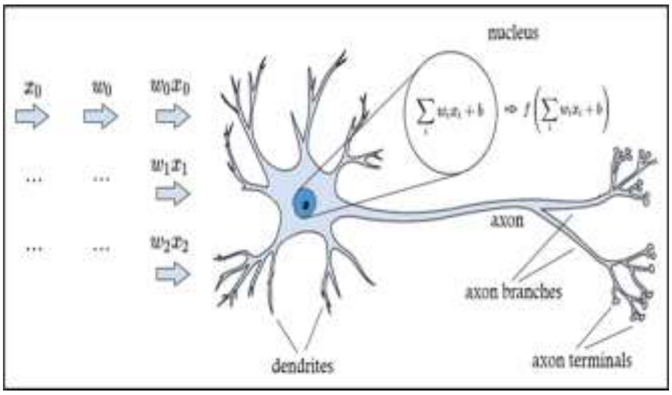


Figure 12. single biological neuron annotated to describe a single artificial neurons function

TABLE 3. Some Difference between (ANN) and (BNN)[22]

| Characteristics | Biological (Real) Neural Network | Artificial Neural Network |
|---|---|---|
| Speed | Processes information at a slower rate. Response time is measured in milliseconds. | Information is processed at a faster rate. The response time is measured in nanoseconds. |
| Processing | Massively parallel processing. processing | Serial processing |
| Size & Complexity | An extremely intricate and dense network of linked neurons of the order of 1011 neurons and 1015 interconnections | Size and complexity are reduced. It is incapable of performing sophisticated pattern recognition tasks. |
| Storage | An extremely intricate and dense network of linked neurons with 1015 interconnections, including neurons on the order of 1011. | The term "replaceable information storage" refers to the practice of replacing fresh data with old data. |
| Fault tolerance | The fact that information storage is flexible means that new information may be added by altering the connectivity strengths without deleting existing information. | Intolerant of faults. In the event of a system failure, corrupt data cannot be recovered. |
| Control Mechanism | There is no unique control mechanism outside of the computational task. | Controlling computer activity is handled by a control unit. |

## X. BASIC TYPES OF ARTIFICIAL NEURAL NETWORK

There are many types of neural networks available, or that might be in the development stage they can be classified depending on their: Structure, Data flow, Neurons used, and their density, Layers, and their depth activation filters [23, 24] such as:

*Feed-forward artificial neural networks:*

One of the first feed-forward artificial neural networks (Figure 13) is a single-layer perception network (Figure 14) [25], which consists of a single layer of output nodes, where inputs are directed to outputs using a sequence of weight values [26].

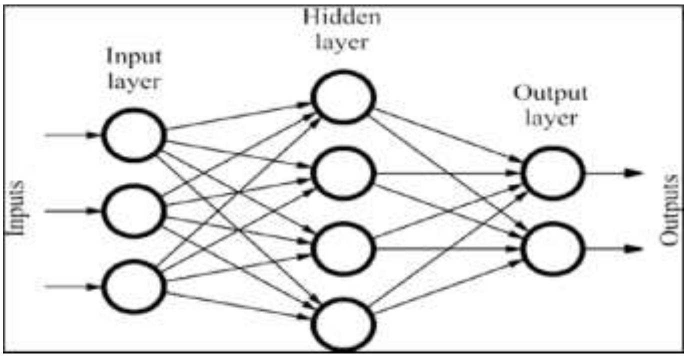


Figure 13. Sample of a feed-forward neural network

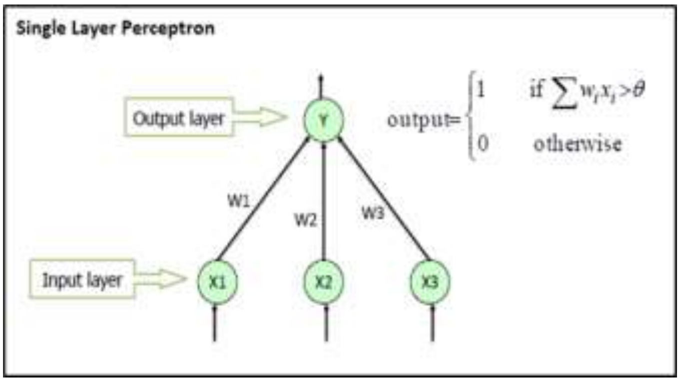


Figure 14. Signal Layer Perception

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*The multi-layer perceptron (MLP):*

The Multilayer perception (Figure 15) [27] is the most popular type of feed-forward artificial neural network. It comprises numerous layers of computational units that are usually integrated feed-forward layer, in which, each neuron in one layer directly links to a neuron in the next layer. In many applications, the units of these networks use a sigmoid function as a transfer function[28]. A multilayer perceptron (MLP) comprises three layers: input, output, and hidden.

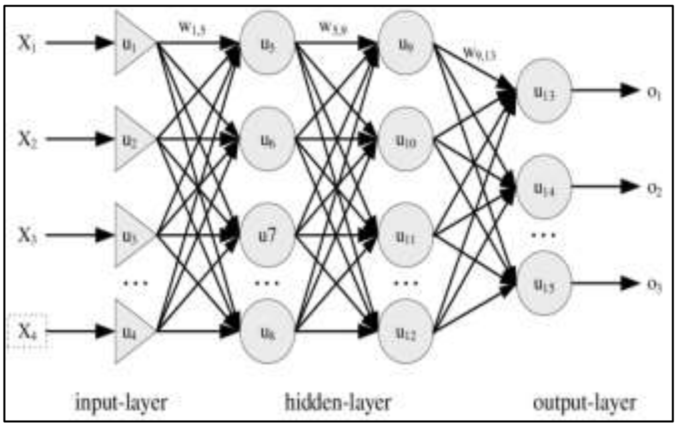

Figure 15. The multi-layer perceptron (MLP)

*Feed Back Neural Networks:*

A feedback neural network is a type of artificial neural network model that has been widely used in signal processing, optimum computation, convex nonlinear programming, seismic data filtering, and other applications. However, traditional feedback neural network models often have time-invariant inputs[29]. With this arrangement, artificial neural networks should not provide input signals to their output layers through hidden layers. Instead, the output signals of neurons are fed back into the input signals, allowing evolution to continue until it is terminated outside. As shown in (Figure 16) [30], feedback artificial neural networks are ideal for optimization problems where the artificial neural network might seek out the optimal arrangement of interrelated elements.

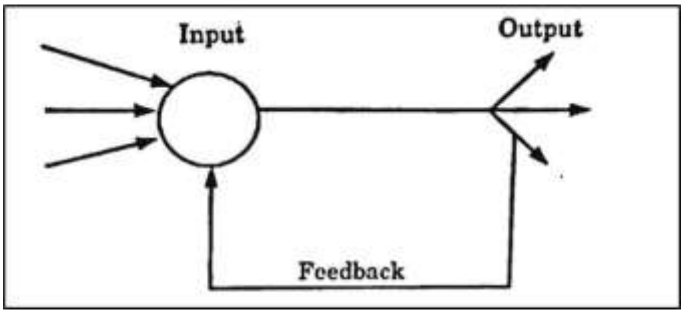

Figure 16. Single node with its own feedback

A feedback neural network is a type of artificial neural network. Competitive learning in artificial neural networks is unsupervised learning where nodes compete for the right to respond to part of the input data [31]. While Artificial Neural Network are a particular machine learning algorithm modeled after the human brain. One of the essential characteristics of an artificial neural network is its ability to learn by interacting with its surroundings or an information source. Learning is typically achieved using an adaptive technique known as a learning rule or algorithm in a neural network [32], such as: -

- Supervised learning also called learning with a teacher or associative learning, involves associating each input pattern/signal received from the environment with an intended goal. At each stage of the learning process, weights are synthesized progressively and modified to reduce the error between the network's output and a corresponding target[33].
- In unsupervised learning, the goal is to identify and categorize specific characteristics or patterns in the training data, with no teacher signal instead. Sometimes, a lower-dimensional collection of patterns is needed. However, any topological relationships between the patterns are preserved[34].
- Reinforcement learning is a trial-and-error method that maximizes the predicted value of a criterion function called the "reinforcement signal". The fundamental concept of reinforcement learning may be traced back to psychology and experimental investigations of animal learning [35]. Reinforcement learning is founded on the premise that if an action (Figure 17)[36] is followed by an "improvement" in the state of circumstances, then the inclination to perform that action is enhanced, i.e., reinforced. Otherwise, the system's propensity to carry out that activity is diminished.

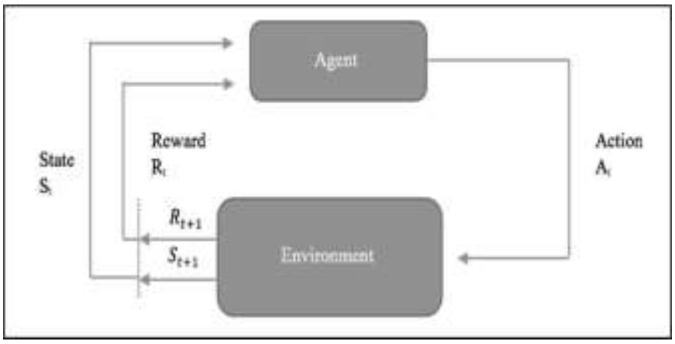

Figure 17. Reinforcement Learning

## XI. BACK PROPAGATION NETWORKS

The Back Propagation (BP) algorithm is one of the most widely used neural network models and method because it is a multilayer feed-forward network (Figure 18)[37]. The BP network may be used to learn and store many mapping relations of an input-output model. In advance, there is no need to disclose the mathematical equation that characterizes these mapping relations. Its learning rule employs the steepest descent approach, with backpropagation used to regulate the network's weight and threshold values to attain the lowest error sum of squares[38]. Backpropagation is an Artificial Neural Networks (ANN) supervised learning method for multilayer feed-forward networks. The backpropagation method works by assuming that a given function is modeled by adjusting the internal weights of the input signals to produce the expected output signal. The difference between the system's output and a known predicted output is supplied to the design and utilized to

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adjust its internal state [39]. Backpropagation is a technique for training the weights in a multilayer feed-forward neural network. As a result, a network structure of one or more levels must be developed, with each layer fully connected to the next. Backpropagation can be used for both classification and regression problems[39]. Backpropagation is a supervised learning process; therefore, the desired outputs are included in the training vector. The actual network outputs are subtracted from the anticipated results, yielding an error signal. The error signal is then used as the starting point for the backpropagation process errors are returned to the neural network by computing the contribution of each hidden processing unit and deriving the necessary modification required to obtain the correct output. The weights of the connections are then modified, and the neural network has just learned from experience. The model can be a simple model with a single output, such as a pricing model, or a sophisticated model with several results, attempting to forecast two or more functions simultaneously.

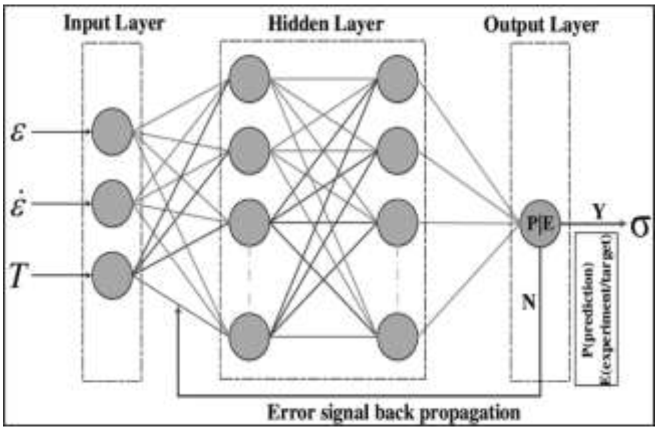

Figure 18. BP-ANN architecture for flow stress prediction

Many other models can be considered in AI including:

- Kohonen Feature
- Probabilistic Neural Networks (PNNs) that provide a scalable alternative to backpropagation neural networks for classification tasks. it offers a supervised training procedure similar to backpropagation that eliminates the necessity for substantial forward and backward calculations associated with conventional neural networks[40].
- General Regression Neural Network (GRNN), which is a one-pass learning technique with a parallel topology; The Counter Propagation Network (CPN) which is a self-programming lookup database with statistically optimal statistics[41]; the Counter Propagation Network (CPN) is a network that learns a bi-directional mapping in hyper-dimensional space for a set of pattern vectors; it understands both a forward mapping and if it exists, inverse mapping.
- Convolutional Neural Network (CNN): is a supervised type of Deep learning, most preferable used in image recognition and computer vision, its compatible with the purpose of research and deals with images recognition. CNN is a deep learning model for processing data, such as grid-shaped images, inspired by the organization of the visual cortex of animals[42], and aims to automatically and adaptively learn a spatial hierarchy of features from low to high. level patterns. A CNN is a mathematical construct consisting of three types of layers (or building blocks): convolutional, pooling, and fully connected. The first two layers, convolution, and pooling extract feature, while the third, a fully connected layer, transfers the extracted features into final outputs like classification. A convolution layer is an important component of CNN, which comprises a stack of mathematical operations such as convolution, a sort of linear operation.

## XII. CNN LAYERS

The CNN architecture is made up of several levels (multi-building blocks). Below in (Figure 19) [43] is a detailed description of each layer in the CNN design, as well as its function.

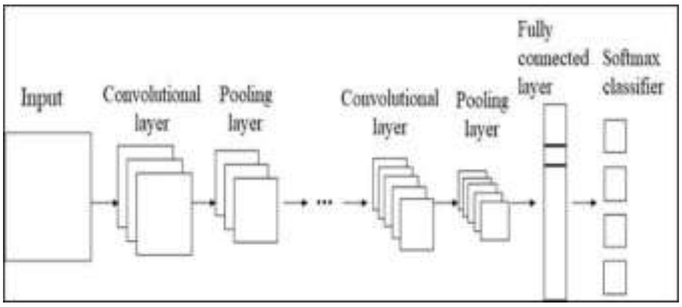

Figure 19. Basic structure of a CNN

*Convolutional Layer:*

The convolutional layer is the most important component of CNN architecture. It is made up of a series of convolutional filters (kernels), that perform feature extraction. It usually contains a combination of linear and non-linear operations, ie. convolution operation and activation function. The input image, described as N-dimensional metrics, is convolved using these filters to form the output feature map[44].

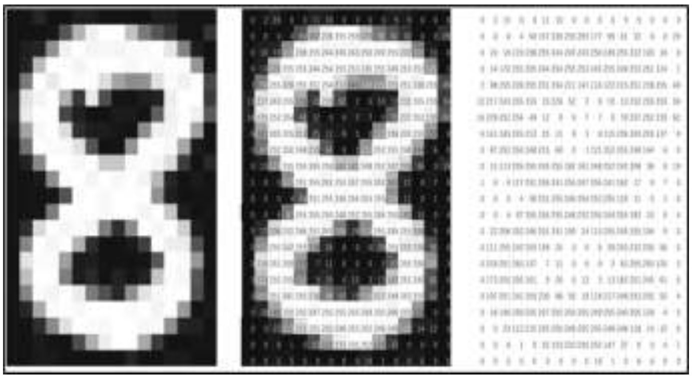
Figure 20. A computer sees an image as an array of numbers

*Kernal:*

In digital images, pixel values are kept in a Two-dimensional (2D) grid, i.e., an array of numbers (Figure 20) [45], and a small grid of parameters called the kernel (Figure 21)[44], and optimizable feature extractor, is applied at each image position, making CNN's particularly efficient for image processing because a feature can occur anywhere in the image. Extracted features can hierarchically and progressively become

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more sophisticated as one layer feeds its output into the next layer. Training is the process of enhancing parameters like kernels to reduce the difference between outputs and ground truth labels using optimization algorithms like backpropagation and gradient descent, among others.

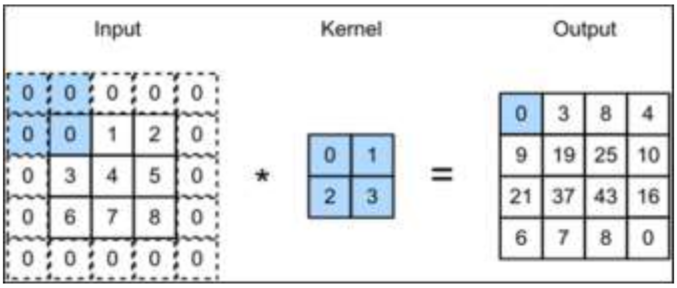


Figure 21. The size of the kernel is (2 * 2)

*Convolution operation:*

Initially, the CNN input format is described, in which, the vector format is the input for the traditional neural network, while a multichannel image is its input. The grayscale images are one-channel, whereas RGB images are three-channel[44]. As an example of the convolutional operation, a (4 * 4) grayscale image with a random-weight-initialized kernel of size (2 * 2). This kernel slides horizontally and vertically across the entire image. The input image and kernel are also combined, where their corresponding values are multiplied and then summed to create a single scalar value, calculated concurrently (Figure 22**Error! Reference source not found.**)[44] depicts t he primary calculations executed at each step in a graphic representation[44].

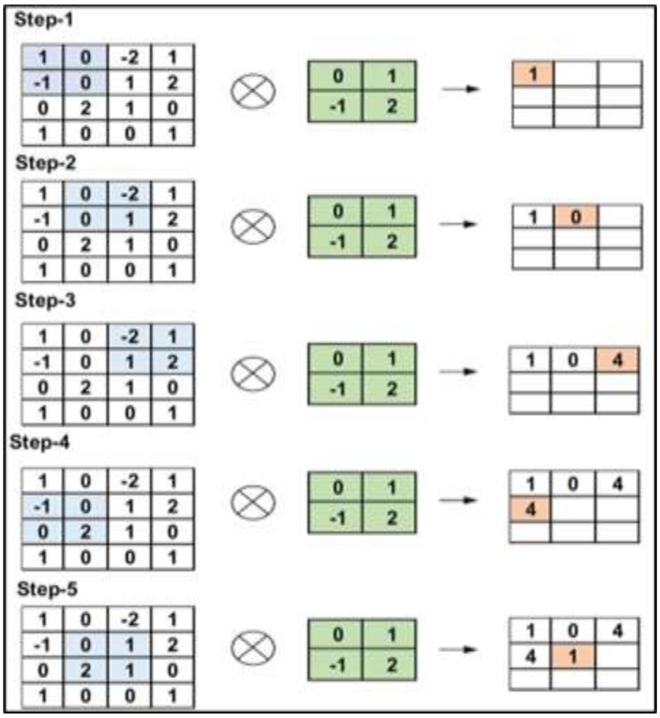


Figure 22. The primary calculations of convolutional layer

*The Stride:*

The stride value determines how far the kernel advances on the input data. If the stride value is two, the kernel moves by two columns of pixels in the input matrix. In other words, the kernel is used to extract high-level features from an image, such as edges[46].

*Pooling Layer:*

The pooling layer's main task is to sub-sample the feature maps generated by convolutional operations. In essence, this process reduces the size of the feature maps, while retaining the most important information or features. Similar, to convolutional operations, the pooling operation involves determining the size of both the stride and the kernel. There are several different types of pooling methods, such as tree pooling, fence pooling, average pooling, minimum reserve, maximum pooling, global average pooling (GAP) and global maximum pooling, all of which can be used for different pools layers.

*Fully connected layers*

A convolutional neural network takes advantage of the fact that an image is made up of tiny elements or features and develops a system for assessing each feature separately to inform a conclusion about the image as a whole [47]. Commonly, this layer is located at the end of each CNN This layer is usually located at the end of any CNN architecture. Within this layer, each neuron is connected to all neurons in the previous layer, a so-called Fully Connected (FC) approach. It is used as a CNN classifier. It follows the basic method of conventional multilayer perceptron neural networks because it is a kind of feedforward ANN. The input to the FC layer comes from the last summation or convolution layer. This input is in the form of a vector created from the feature maps after flattening. The output of the FC layer represents the final CNN output, as illustrated in (Figure 23) Completely connected layers of a CNN are not to be confused with fully connected neural networks - the conventional neural network architecture in which all neurons connect to all neurons in the following layer.

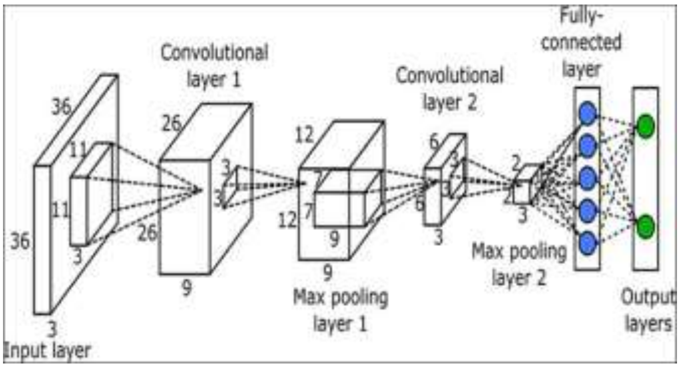


Figure 23. Fully connected layer

Deep learning for computer vision is made possible by convolutional neural networks. For computer vision applications, the conventional neural network architecture was inefficient. Images are a significant input source for a neural network (they can have hundreds or thousands of pixels and up

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to 3 color channels). This necessitates many connections and network characteristics in a traditional, fully connected network [47].

## XIII. Case Study Analytical and Descriptive Methodology Approach

The Case study was conducted on a part of the Gazira scheme (2,200,000 acres) in Sudan. The study area was about (139871.87 acres) Located on Al Kamlin Locality of Al Gazira State lies between latitudes 15.291964 ° N to 15.047787 ° N and longitudes 32.896518 °E to 33.091627 °E (Figure 24). From this study area, several types of geospatial data have been used in which the data was a combination of satellite images Sentinel-2 for multiple dates and ground truth data obtained from field visits. the imagery data obtained from the USGS website. All data are in a metric unit's systems based on Universal Transverse Mercator (UTM) projection, zone 36N.

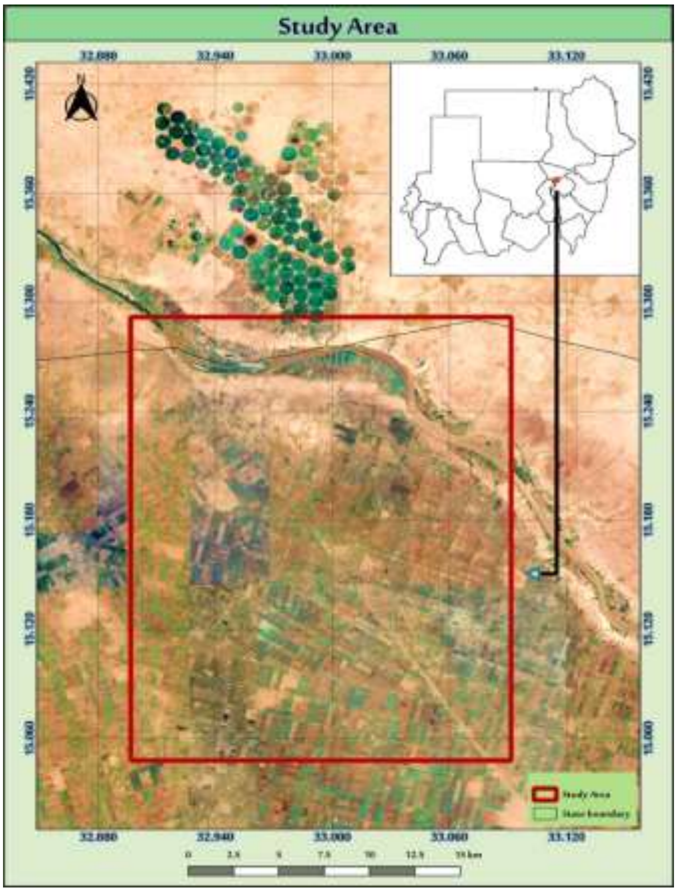


Figure 24. Study Area

TABLE 4. Case Study Raster Data

| Name | Date | Source | Used Bands |
|---|---|---|---|
| **T36PVB_2019-09-30T115637** | 2019-09-30 | USGS - Earth Explorer | 13 bands |
| **T36PVB_2019-10-25T102425** | 2019-10-25 | USGS - Earth Explorer | 13 bands |
| **T36PVB_20191010T080839** | 2019-10-10 | USGS - Earth Explorer | 13 bands |
| **T36PVB_20191015T080911** | 2019-10-15 | USGS - Earth Explorer | 13 bands |
| **T36PVB_2019-09-30T115637** | 2019-09-30 | USGS - Earth Explorer | 13 bands |

The methodology was based on two main approaches; analytical and descriptive approaches with their two phases: Phase One the planning and data preparation phase, and Phase two the Machine Learning implementation phase, their various steps were described in (Figure 25) and (Figure 26) using QGIS software in phase one to process and prepare the Data. This Phase is followed by the second phase (Phase Two), the implementation of the artificial intelligence network and utilization of the data extracted from satellite images of the study area. The Conventional Neural Network (CNN) method had been chosen to be used in this Case study, due to its powerful structure in dealing with image recognition and image classification.

TABLE 5. Case Study Vector Data

| Name of layers | Date |
|---|---|
| North Gazira Boundary (Study Area) | - |
| Ground truth data | **2019** |
| Roads | - |
| Localities | - |

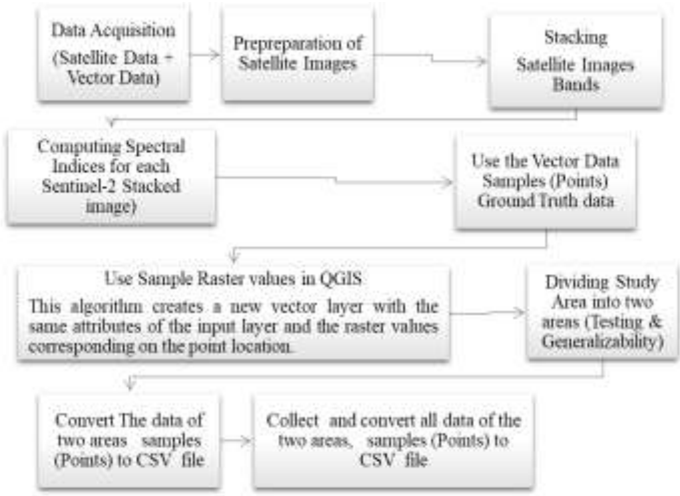


Figure 25. phase One The planning and data preparation

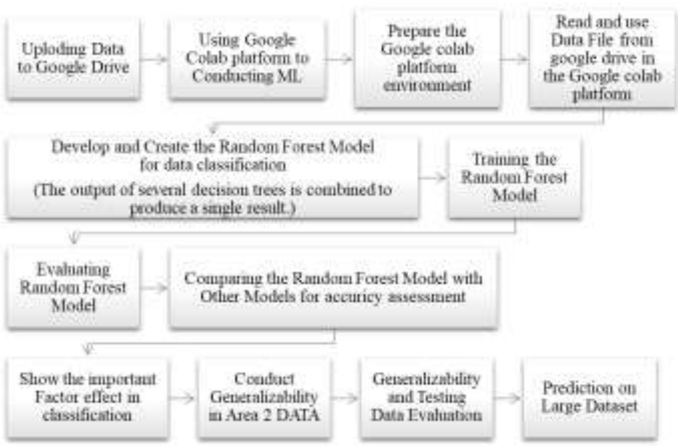


Figure 26. Phase Two implementing the Machine learning model

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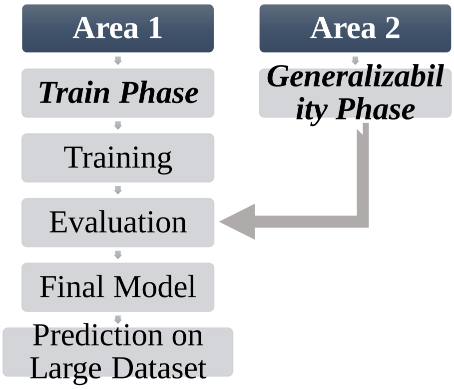


Figure 2. Machain learning model steps

## XIV. SPECTRAL INDICES

Spectral indices are used to enhance certain features or characteristics of the earth's surface, such as vegetation, soil, water. There it was developed based on the spectral properties of the object of interest [48]. Numerous spectral indices can be used to examine various factors. Sentinel-2 images have the ability to execute numerous operations on their bands, the results of which can be translated into spectral indices. This is done using map algebra (Raster calculator) to solve a series of equations that will assist in study.

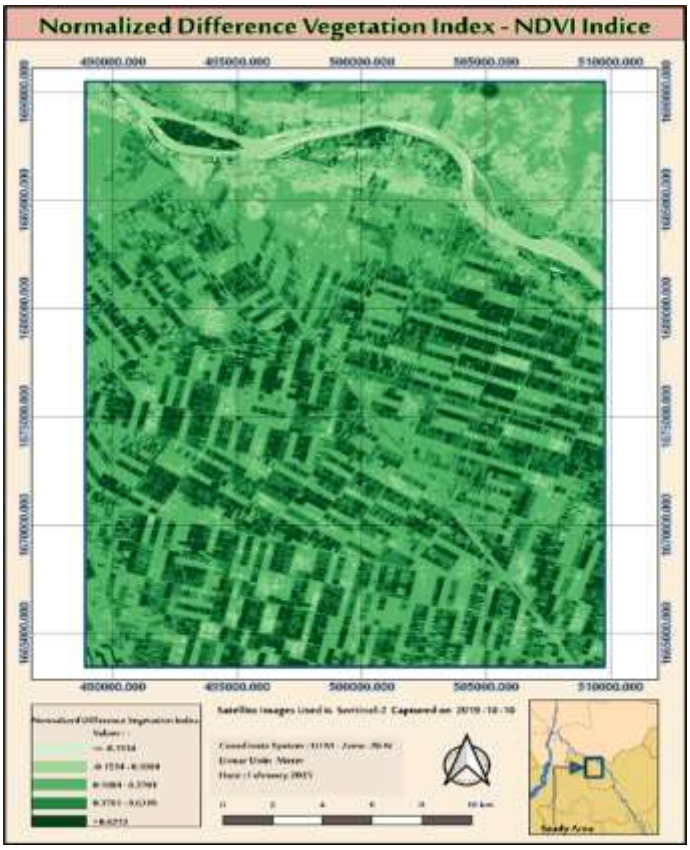


Figure 28. Study Area Normalized Difference Vegetation Index

*Normalized Difference Vegetation Index (NDVI)*

Normalized Difference Index of Vegetation (NDVI): Spectral indices dedicated to vegetation analysis are developed according to the principle that healthy vegetation strongly reflects in the near infrared (NIR) spectrum and strongly absorbs in the visible red [48]. the Normalized Difference Vegetation Index (NDVI) is a numerical indicator that employs the red and near-infrared spectral bands to assess vegetation health. NDVI is strongly linked to vegetation content. Areas with higher NDVI values reflect more in the near-infrared spectrum. Higher near-infrared reflectance indicates denser and healthier vegetation[49]. The NDVI indices are computed for each image based on the equation (1) and represented on (Figure 28)

$$\boldsymbol{NDVI} = (\boldsymbol{B08} - \boldsymbol{B04}) / (\boldsymbol{B08} + \boldsymbol{B04}) \quad \text{------------------------------------(1)}$$

B04 = Red, B08= Near-infrared (NIR)

*Soil Adjusted Vegetation Index (SAVI)*

SAVI is used to adjust the Normalized Difference Vegetation Index (NDVI) for the influence of soil brightness in areas with low vegetation cover (Figure 29). Surface Reflectance derived from Sentinel-2. SAVI is derived as a ratio of the R and NIR values, with a soil brightness correction factor (L) of 0.428 to account for the majority of land cover types[49]. The SAVI indices computed for each image based on equation (2) and represented on (Figure 29).

$$\boldsymbol{SAVI} = (\boldsymbol{B08} - \boldsymbol{B04}) / (\boldsymbol{B08} + \boldsymbol{B04} + \boldsymbol{0.428}) * (\boldsymbol{1.428}) \quad \text{----------------------(2)}$$

B04 = Red, and B08= Near-infrared (NIR)

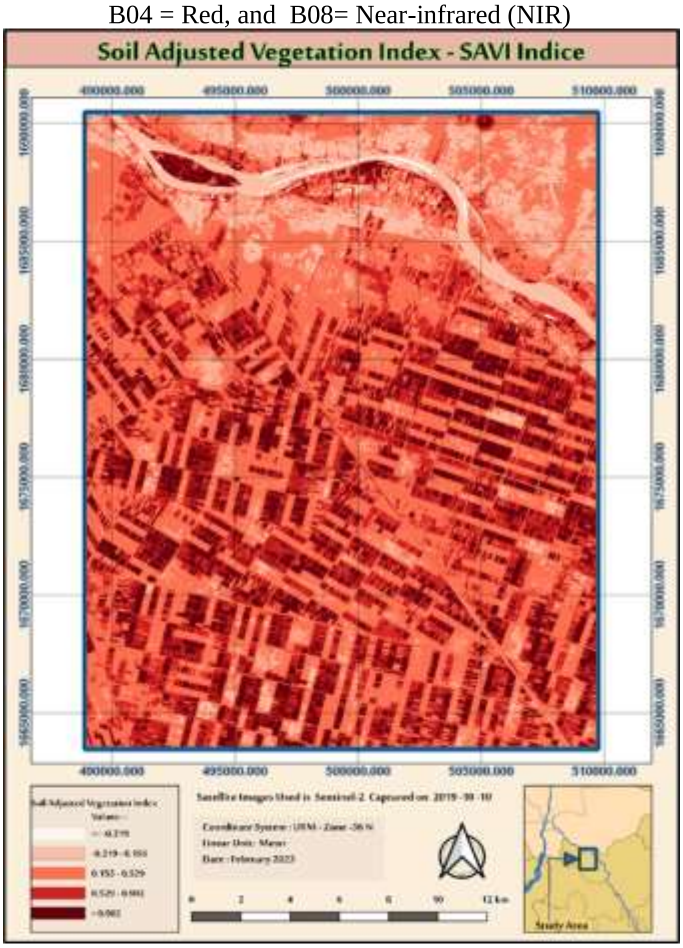


Figure 29. Study Area Soil Adjusted Vegetation Index

*Advanced Vegetation Index (AVI)*

It is a numerical indicator that uses the red and near-infrared spectral regions, similar to NDVI. AVI, like NDVI, is used in vegetation studies to track agricultural and forest variations over time. Users can distinguish different types of vegetation and extract phenology characteristics/parameters using the multi-temporal combination of the AVI and the NDVI [49]. The SAVI indices computed for each image based on the below equation (3) and represented on (Figure 30).

$$\mathbf{AVI} = [\mathbf{B8} * (\mathbf{1} - \mathbf{B4}) * (\mathbf{B8} - \mathbf{B4})]^{1/3} \quad \text{-------------------(3)}$$

B04 = Red, and B08= Near-infrared (NIR)

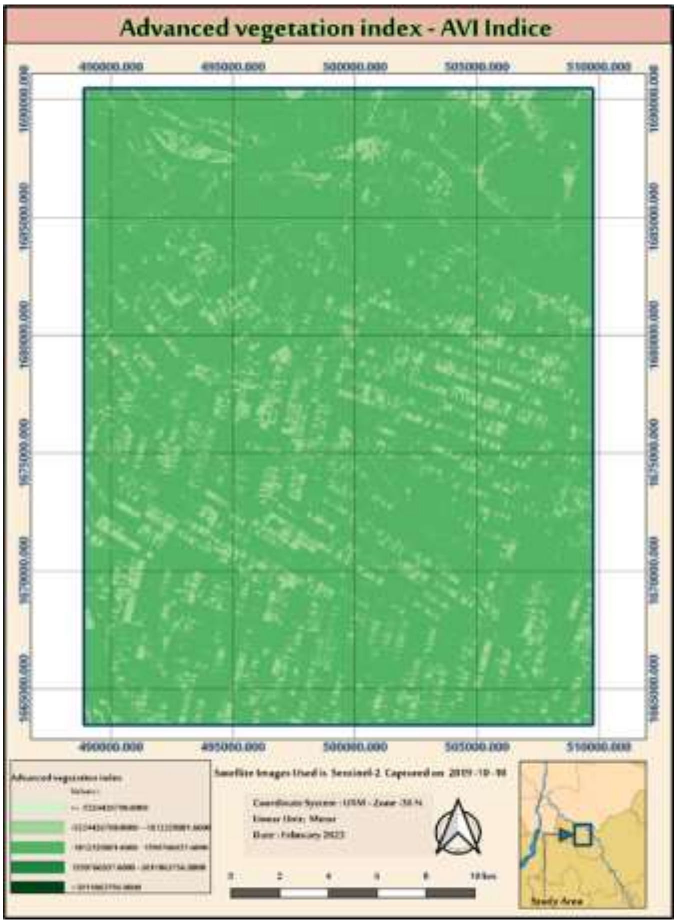


Figure 30. Study Area Advanced Vegetation Index

## XV. CONCLUSION

The paper aims to highlight the Artificial Intelligence Network approaches as modern techniques for crops classification and for designing a model that supports the correct classification to reduce the time, effort, and costs of crops classification. The methodology used was relied on the analysis, planning and design stages. In the case study, at the analysis stage, the problem tree and the vision tree were created; and the strategies for possible solutions by using free Sentinel-2 remote sensing satellite images are presented. The planning and design stage consisted of developing the framework design to reach the pre-determined goal by the agreed strategy, and to prepare the schedule and maps. The classification was implemented through monitoring and evaluation of the methods used in the classification. QGIS software was used to process the imagery, and the vector data and make a compilation from images and vector data that contain a specific crop and converted it to a CSV file that presented the study area after computing the Spectral Indices for the selected target image, dated October 2019. The Advanced Vegetation Index (AVI) as a numerical indicator that uses the red and near-infrared spectral regions, similar to NDVI. AVI, like NDVI, is used in vegetation studies to track agricultural and forest variations over time. Different types of vegetation and extract phenology characteristics/parameters can distinguished using the multi-temporal combination of the AVI, the NDVI, and the SAVI indices computed for each image.

## REFERENCES

[1] Jorge Mendes , T.M.P., Filipe Neves Dos Santos, R. MoraisMario Cunha. *Smartphone Applications Targeting Precision Agriculture Practices—A Systematic Review*. June 2020, May 2024 10:25 PM; Available from: https://www.researchgate.net/profile/Mario-Cunha-2/publication/342221374/figure/fig1/AS:903260533706752@1592365501404/Information-needed-from-farmers-through-the-agricultural-cycle-Adapted-from-Reference.ppm.

[2] Mahgoub, F., *Current status of agriculture and future challenges in Sudan*. 2014: Nordiska Afrikainstitutet.

[3] Atkinson, P.M. and P. Aplin, *Spatial variation in land cover and choice of spatial resolution for remote sensing.* International Journal of Remote Sensing, 2010. 25(18): p. 3687-3702.

[4] GISGeography. *Image Classification Techniques in Remote Sensing [Infographic]*. 26-05-2022; Available from: https://gisgeography.com/image-classification-techniques-remote-sensing/.

[5] Baranova, K. *SUPERVISED IMAGE CLASSIFICATION* May 20 2020 10:30 PM; Available from: https://blogs.ubc.ca/katerynabaranovasgis/2016/11/03/supervised-image-classification/.

[6] Ismail, M.H., H.Z. Pakhriazad, and K. Norlida, *Remote Sensing for Mapping RAMSAR Heritage Site at Sungai Pulai Mangrove Forest Reserve, Johor, Malaysia.* Sains Malaysiana, 2011. 40: p. 83-88.

[7] GISGeography. *OBIA – Object-Based Image Analysis (GEOBIA)*. 26-05-2022; Available from: https://gisgeography.com/obia-object-based-image-analysis-geobia/.

[8] Jwan Al-doski, S.B.M., Helmi Zulhaidi Mohd Shafri, *Image Classification in Remote Sensing.* Journal of Environment and Earth Science, 2013. 3(10, 2013).

[9] Documentation, Q. *Raster Data*. Available from: https://docs.qgis.org/3.4/en/docs/gentle_gis_introduction/raster_data.html.

[10] Schmedtmann, J. and M. Campagnolo, *Reliable Crop Identification with Satellite Imagery in the Context of Common Agriculture Policy Subsidy Control.* Remote Sensing, 2015. 7(7): p. 9325-9346.

[11] GISGeography. *Passive vs Active Sensors in Remote Sensing*. March 10, 2024; Available from: https://gisgeography.com/passive-active-sensors-remote-sensing/.

[12] Reddy, M.A., *Textbook of Remote Sensing and Geographical Information Systems* 2008. p. 476.

[13] Marr, B. *What Are Artificial Neural Networks - A Simple Explanation For Absolutely Anyone*. Sep 24, 2018,12:46 am EDT 7/6/2024 12:44 PM; Available from: https://www.forbes.com/sites/bernardmarr/2018/09/24/what-are-artificial-neural-networks-a-simple-explanation-for-absolutely-anyone/?sh=4295f9412457.

[14] Skansi, S., *Introduction to Deep Learning: from logical calculus to artificial intelligence*. 2018: Springer.

[15] Gill, N.S. *Artificial Neural Networks Applications and Algorithms*. 2021; Available from: https://www.xenonstack.com/blog/artificial-neural-network-applications.

International Journal of Scientific Engineering and Science
Volume 8, Issue 6, pp. 122-134, 2024. ISSN (Online): 2456-7361

[16] Baheti, P., *The essential guide to neural network architectures.* Dostupné z: https://www. v7labs. com/blog/neural-network-architectures-guide, 2022.
[17] Ghahnavieh, A.E., *Time series forecasting of styrene price using a hybrid ARIMA and neural network model.* Independent Journal of Management & Production, 2019. 10(3): p. 915.
[18] Radhakrishnan, R. *What Are the 4 Main Functions of the Nervous System?* 2021; Available from: https://www.medicinenet.com/4_main_functions_of_the_nervous_system/article.htm.
[19] Krenker, A., J. Bešter, and A. Kos, *Introduction to the artificial neural networks.* Artificial Neural Networks: Methodological Advances and Biomedical Applications. InTech, 2011: p. 1-18.
[20] Yacim, J. and D. Boshoff, *Impact of Artificial Neural Networks Training Algorithms on Accurate Prediction of Property Values.* Journal of Real Estate Research, 2018. 40: p. 375-418.
[21] ZENDONEW, T. *Hidden Layer*. Available from: https://deepai.org/machine-learning-glossary-and-terms/hidden-layer-machine-learning#:~:text=In%20neural%20networks%2C%20a%20hidden,inputs%20entered%20into%20the%20network.
[22] Thakur, A., *Fundamentals of Neural Networks.* International Journal for Research in Applied Science and Engineering Technology, 2021. 9(VIII): p. 407-426.
[23] Shao, C., *A Quantum Model for Multilayer Perceptron.* arXiv: Quantum Physics, 2018.
[24] He, X. and S. Xu, *Feedback Process Neural Networks*, in *Process Neural Networks: Theory and Applications*, X. He and S. Xu, Editors. 2010, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 128-142.
[25] saedsayad. *Artificial Neural Network - Perceptron*. 8-6-2024 9:00 AM; Available from: https://www.saedsayad.com/artificial_neural_network_bkp.htm.
[26] Mohammad, A.H., T. Alwada'n, and O. Al-Momani, *Arabic Text Categorization Using Support vector machine, Naïve Bayes and Neural Network.* GSTF Journal on Computing (JoC), 2016. 5(1).
[27] Permanasari, A., A. Chamsudin, and O. Wahyunggoro, *Utilization of Neural Network for Disease Forecasting*. 2013.
[28] Shao, C., *A quantum model for multilayer perceptron.* arXiv preprint arXiv:1808.10561, 2018.
[29] He, X. and S. Xu, *Feedback process neural networks.* Process Neural Networks: Theory and Applications, 2010: p. 128-142.
[30] Joshi, A. *Neural Network For Beginners*. Apr 3, 2022 8/6/2024 10:00 AM; Available from: https://akashjoshirm-aj.medium.com/neural-network-for-beginners-accb6fc1d1ab.
[31] *Competitive learning*. 8/6/2024 10:15 AM; Available from: https://www.wikiwand.com/en/Competitive_learning.
[32] Hassoun, M.H., *Fundamentals of Artificial Neural Networks*. MIT Press, 1995.
[33] Hassoun, M.H., *Supervised Learning in a Single Unit Setting*. MIT Press, 1995.
[34] Hassoun, M.H., *Unsupervised Learning*. June 5 2020 , 10:30 PM, MIT Press, 1995.
[35] Hassoun, M.H., *Reinforcement Learning*. June 5 2020 , 11:00 PM, MIT Press, 1995.
[36] Haney, B.S. *Reinforcement Learning*. Available from: https://medium.com/@brian.s.haney44/reinforcement-learning-5d578a0de1ff.
[37] Kostadinov, S., *Understanding Backpropagation Algorithm*. Aug 8, 2019 , May 4 2024 10:30 PM, Towards Data Science: Towards Data Science.
[38] Li, J., et al. *Brief Introduction of Back Propagation (BP) Neural Network Algorithm and Its Improvement*. in *Advances in Computer Science and Information Engineering*. 2012. Berlin, Heidelberg: Springer Berlin Heidelberg.
[39] Brownlee, J. *How to Code a Neural Network with Backpropagation In Python (from scratch)*. 2021; Available from: https://machinelearningmastery.com/implement-backpropagation-algorithm-scratch-python/.
[40] Mohebali, B., et al., *Chapter 14 - Probabilistic neural networks: a brief overview of theory, implementation, and application*, in *Handbook of Probabilistic Models*, P. Samui, et al., Editors. 2020, Butterworth-Heinemann. p. 347-367.
[41] Hecht-Nielsen, R., *Counterpropagation networks.* Appl Opt, 1987. 26(23): p. 4979-83.
[42] Laming, D., *Nonlinearity that enables the perception of counterphase flicker.* JOSA A, 2022. 39(1): p. 28-31.
[43] You, W., et al., *An intelligent deep feature learning method with improved activation functions for machine fault diagnosis.* IEEE Access, 2019. 8: p. 1975-1985.
[44] Alzubaidi, L., et al., *Review of deep learning: concepts, CNN architectures, challenges, applications, future directions.* Journal of big Data, 2021. 8: p. 1-74.
[45] Al-Yasriy, H.F., et al. *Diagnosis of lung cancer based on CT scans using CNN*. in *IOP Conference Series: Materials Science and Engineering*. 2020. IOP Publishing.
[46] geeksforgeeks. *Types of padding in convolution layer*. 23 Apr, 2023 8/6/2024 11:00 AM; Available from: https://www.geeksforgeeks.org/types-of-padding-in-convolution-layer/.
[47]. Hao, W., et al. *The role of activation function in CNN*. in *2020 2nd International Conference on Information Technology and Computer Application (ITCA)*. 2020. IEEE.
[48] Valerio Tramutoli, N.C., Valeria Satriano – University of Basilicata; Sara Wiman, Greger Lindeberg – Geografiska, *Sentinel-2 data and vegetation indices*, in *EO4GEO Lecture*. 2020-09-14 9/6/2024 1:45 AM.
[49] Gabri. *List of spectral indices for Sentinel and Landsat*. September 17, 2019 Available from: https://giscrack.com/list-of-spectral-indices-for-sentinel-and-landsat/.