An Overview Of Artificial Intelligence Systems

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***Abstract*— The electrical devices and electronics that surround us are getting smarter as technology develops. Machines that mimic human intelligence and cognitive processes like learning and problem-solving are referred to as artificial intelligence. This research examines artificial neural networks, a prominent approach to logical computation. Neural networks are a desirable tool for work because of their success and ease of implementation in various application areas.**

***Keywords*— artificial intelligence, neuron networks, machine learning**

I. INTRODUCTION

Technology has grown increasingly integrated into our daily lives over time. Businesses are increasingly using machine learning algorithms, sometimes known as artificial intelligence (AI), to meet the rapid changes in consumer expectations. Models of artificial neural networks underlie many of the most intricate machine learning applications. They address a wide range of issues, which suggests that there are many different kinds of artificial neural networks. Data flow, network architecture, and complexity are among the factors that categorize them. Modeling and attempting to replicate neuronal function to enhance machine learning is the ultimate objective, regardless of the type of network. Software programs known as neural networks mimic the human brain's decision-making process. They accomplish this by employing mechanisms that resemble the way biological neurons cooperate to recognize events, weigh possibilities, and draw conclusions [1], [2]. Neural networks have gained popularity recently, both in university-level scientific research and in the development of valuable commercial goods. Numerous fields, including computer science, robotics, trade, medicine, mathematics, and automatic control systems, heavily rely on them. The voice assistants Alexa and Siri are among the most popular, well-known, and widely used devices. AI technologies are the foundation of both Alexa and Siri [3]. Neural networks get their name because neurons form the basis of their structure. The structure of a neuron, which defines a nonlinear, restricted algebraic function whose value depends on parameters known as coefficients or weights, is visually depicted in Fig. 1. The function's "inputs" are the variables that make it up, and its value is the "output" [4], [9].

Figure 2 shows an example of a neural network, which is a collection of neurons that are "connected" to one another and allow information to flow from the input to the output without the need for "feedback." Artificial neurons or several node layers may make up the final neural network [5]. These consist of an output layer, one or more hidden layers, and the so-called input layer.

A database is necessary for training a neural network in order for it to function accurately and precisely. We carry out this training frequently over time until we achieve an ideal degree of accuracy. Only then can the network provide rapid grouping and classification of data.

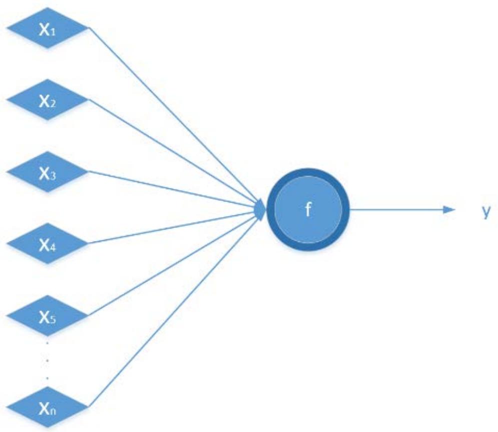

Fig. 1. Neuronal graphic structure.

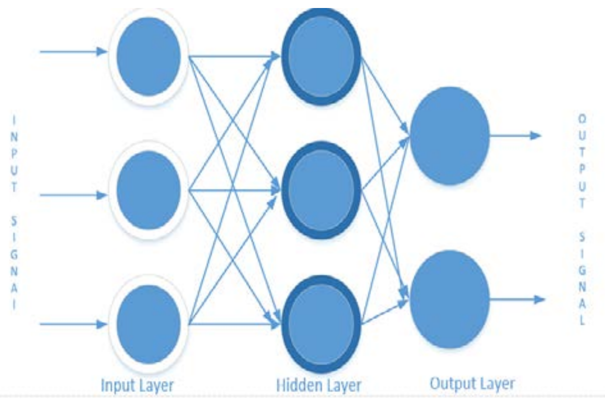

Fig. 2. One hidden layer neural network

The criteria by which the model's efficacy will be assessed must be established at the outset of the model-building process because they can greatly influence the model architecture and weight optimization strategies that are used. Training data and independent validation data are the two subsets of the available data. The training and validation data must be representative of the same population to get more accurate findings. Poor prediction outcomes should be anticipated when working with a small number of input data points since it may be challenging to gather a representative validation set. Therefore, the network must be constructed with as much input data as possible to produce more dependable outputs.

The number of weights and the manner in which information moves through the network are decided by the network architecture. In the process of creating a model, choosing the right network architecture is one of the most crucial—and challenging—tasks. The weight of a particular variable determines its significance. Passing the output via an activation function, which determines the output, is the next stage in creating a neural network. If the output value exceeds a predetermined threshold, the node activates and passes the data to the next network layer. Consequently, one node's output becomes the subsequent node's input. The way data flows from one layer to the next makes this neural network a propagation network [6].

A loss function serves as the foundation for artificial neural network optimization. A loss function is the discrepancy between the output that was expected and what actually happened. Since they establish whether the model has been trained optimally or suboptimally, the criteria used to determine "when to stop the training process" are crucial. Training usually stops when the error gets to a small enough value or when the training error changes little. We need to verify the trained network's performance using the chosen criteria on a separate data set after the training (optimization) stage.

Even as the model is being trained, the so-called mean square error (MSE) can be calculated. The objective is to guarantee the accuracy of every observation by minimizing the mistake as much as feasible. The model employs reinforcement learning to arrive at a local minimum as it modifies its weights and biases. Gradient descent is the method by which the algorithm modifies its weights, enabling the model to decide which course to pursue to minimize mistakes. Every training case smoothly tunes the model parameters to the minimum.

II. Mathematical Image Of The Neural Network

Every neural network has a basic unit, the so-called artificial neuron, which is a mathematical model that imitates the work of a biological neuron [9,10]. Each neuron takes input values, applies weights to them, sums them, and passes the result through an activation function [11]. The calculations in a neuron can be described by the following formula:

$$z = \sum_{i=1}^{n} w_i . x_i + b \tag{1}$$

Where:
x_i - the input values to the neuron,
w_i - the weights associated with each input,
b - the bias,
z- the linear combination of the inputs.

After calculating the linear sum, the value z is fed to an activation function ϕ(z), which determines the output of the neural network (2).

$$a = \phi\ (z) \tag{2}$$

Activation functions introduce nonlinearity into the model and allow the network to learn complex relationships. Commonly used functions include the sigmoid function (3), the ReLU (Rectified Linear Unit) (4), and the hyperbolic tangent (5).

$$\phi\ (z) = \frac{1}{1+\mathrm{e}^{-z}} \tag{3}$$

$$\phi\ (z) = \max\ (0, z) \tag{4}$$

$$\phi\ (z) = \tanh(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}} \tag{5}$$

The neural network training process involves optimising the loss function, which measures the difference between the predicted and actual values. Regression commonly employs the mean square error (MSE), as mathematically described by (6).

$$L = \frac{1}{m} \sum_{i=1}^{m} (y_i . \hat{y}_i)^2 \tag{6}$$

Where:
y_i – is the real value,
$\hat{y}_i$ – expected implied value,
m – number of observers.

To minimise this function, gradient descent and backpropagation are applied, in which the partial derivatives of the losses with respect to the weights are calculated and their values updated. It is described by (7).

$$w_j = w_j - \eta \frac{dL}{dw_j} \tag{7}$$

Where:
η- is learning rate.

III. Types Of Neural Networks

Neural network types are used for a variety of purposes. For "shallow" machine learning, the traditional neural network relies on human intervention to enable the computer system to recognise patterns, learn, carry out particular tasks, and produce precise results. Developed by Frank Rosenblatt in 1958, the perceptron is the oldest neural network [7]. Numerous modifications have been made to its construction, resulting in the well-known architecture seen in Figure 3.

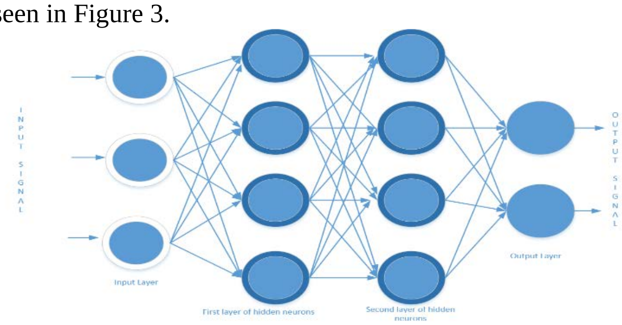

Fig. 3. Perceptron architecture with two hidden layers

A large portion of the feature extraction process is automated via so-called deep learning, which removes some of the need for manual human interaction (Fig. 4). This type of training can utilize large data sets. This group of perceptrons includes multilayer ones. An input layer, one or more hidden layers, and an output layer make up multilayer perceptrons (MLPs). Although these neural networks are also frequently referred to as MLPs, it is crucial to remember that they are made up of sigmoid neurons rather than perceptrons because the majority of the problems they must answer are nonlinear. The majority of deep neural networks flow from input to output in a single direction, called feedforward. Feedback can also train the model, causing the neurons to flow from output to input in the opposite direction. Through this kind of training, the model's performance can be improved and its parameters changed.

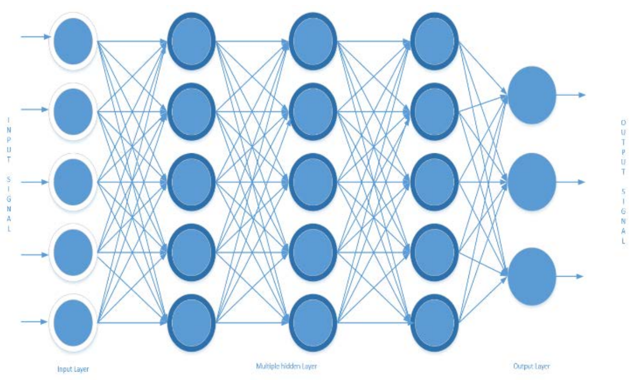

Fig. 4. Deep neural network

One kind of feedforward network that is specifically designed for image processing and analysis is the convolutional neural network (CNN). They are frequently employed in tasks like visual object classification, computer vision, and image recognition. To extract distinctive features and arrive at the intended outcome, their method of operation involves gradually transforming the image's pixel values over successive layers. To find patterns and structures in an image, CNN networks employ mathematical operations from linear algebra, primarily those associated with matrix multiplication and convolutions. Feedback loops, which enable recurrent neural networks (RNNs) to process sequential data and preserve information about past states, are a defining feature of RNN architecture. In time series research and forecasting, such as when tracking market movements, making stock market predictions, or examining sales data, this kind of network is frequently utilized. Neural networks can be categorized into various groups based on their design and function, as table 1 illustrates.

The development of artificial intelligence (AI) is just entering its key phases, and although it has already achieved significant progress in the specified field, its potential is far from exhausted. Modern AI systems demonstrate high efficiency in performing narrowly specialised tasks, but the aspiration of the scientific community is to build universal intelligent systems capable of self-learning, adapting, and making decisions in unfamiliar contexts [12].

Forecasts from leading researchers indicate that by the middle of the 21st century, we can expect the onset of the so-called technological singularity— the moment when AI will surpass human intelligence in capacity and adaptability [8], [12]. In this context, the distinction between narrow, general, and superintelligent AI is of particular importance, since each of these levels represents a degree of autonomy, universality, and cognitive power.

TABLE I
UNITS FOR MAGNETIC PROPERTIES

Neuron networks type	Application
Feedforward Neural Network (FNN)	Basic type for tabular data and regression
Convolutional Neural Network (CNN)	Image/video recognition
Recurrent Neural Network (RNN)	Time series analysis, texts
LSTM / GRU	More robust RNNs, e.g. for translation, chatbots
Autoencoder	Compression, denoising
GAN (Generative Adversarial Network)	Generation of new images/video

As a starting point in this development, the so-called artificial narrow intelligence (ANI) stands out. It is characterized by being narrowly specialized in a specific area and solving a well-specified task. According to the singularity theory of [8], artificial intelligence will continue to develop and improve, as shown in Fig. 5.

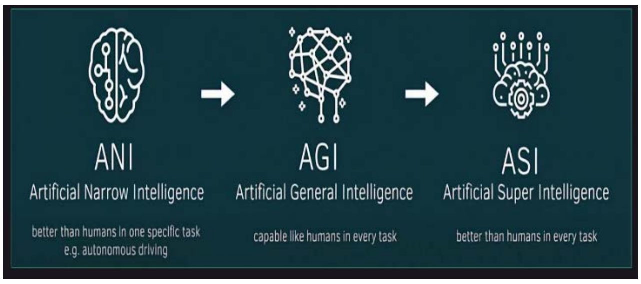

Fig. 5. Kurtzweil's singularity theory

It is assumed that in 2029 we will reach artificial general intelligence, AGI. This involves universal knowledge, which will be able to solve any human task in any context. It is assumed that AGI will be trained to think and create at the level of humans.

The pinnacle in the field of artificial intelligence is artificial super intelligence, ASI. Kurtzweil suggests that the era of ASI will come in 2045. The attitudes are that it will have human self-awareness. It will implement goals, desires, and emotions. It will make all kinds of decisions and experience all human sensations. With its ability to analyze and remember, it is expected to be infinitely better than humans.

IV. CONCLUSION

To make the presentation clear and accessible, the goal is to give enough precise information without going into intricate mathematical details. A well-liked and successful method for applying artificial intelligence to various activities is the use of neural networks. They are used in many different fields of science and practice, including engineering, finance, medicine, and many more. Its ability to self-learn is a major benefit, as it helps them become more accurate and flexible while validating results.

When given the right structure and training, a neural network's so-called universal approximation ability enables it to represent (or approximate) any continuous function with arbitrary precision.

Neural networks are a powerful and flexible tool for processing complex and unstructured data. They are characterized by high accuracy, self-learning ability, and application in various fields, making them a key technology in the field of artificial intelligence.

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