Using Artificial Neural networks wireless to implement Machine Learning

Hassan M. Ibrahim

University of Information Technology and Communications, Baghdad, Iraq
hassan.m@uoitc.edu.iq

ABSTRACT

In order to successfully deliver ubiquitous Internet connectivity, wireless networks can support the Internet of Things (IoT)use machine learning concepts integrated across the wireless core to allow intelligent, data-driven functions edge technology Machine learning techniques based on (ANNs) can resolving different wireless networking issues. To achieve this, we first give a thorough rundown of several important categories of recurrent, spiking, and deep neural network-based ANNs, uses of wireless networking that are relevant. For every kind of ANN, we present both the fundamental architecture and particular Examples for wireless networks that are very significant design. Long short-term memory, liquid state machines, and echo state networks are a few examples of this type. Then, we give a thorough review of the various wireless communication issues that can be solved with ANNs, covering anything from. We list future projects that can be addressed using ANNs, as well as the major reasons for employing them, for each unique application.

Keywords: Artificial neural network; machine learning; Convolutional neural networks; Deep Belief Network

1- Introduction:

A major transformation is taking place in the world of wireless networks. Wearable devices are gradually being integrated into the smartphone-centric networks of the past, giving rise to the Internet of Things (IoT) as well as causing this extraordinary shift in the emergence of new and unproven wireless service use cases that differ significantly from the current [1][2].

There is a large body of studies examining what the ideal cellular network architecture is due to the need to deal with the continuous and rapid expansion of wireless services. While core components of the 5G network have been discovered, such as dense device-to-device (D2D) communications, small cell deployments, and wave communications, their combination is essential to address IoT problems and implement smart network features, optimizing and ensuring quality of service requirements for developing Wireless and IoT services in a real-time and adaptive manner to machine learning based on artificial neural network [3][4].

1.1 Role Of Anns In Wireless Networks

As demonstrated by the widespread use of ML in numerous application fields Unquestionably, ML technologies are among the most important tools for adding intelligent features to wireless networks. Machine learning (ML) Any wireless device will be able to actively and intelligently monitor its environment with the help of wireless networks by learning to predict features for example, remote channel elements, traffic designs, network organization, content solicitations, client setting, and so on. Proactive measures to increase the likelihood to some definable goal, will be achieved [5][6]. With the help of machine learning, the network infrastructure may put adaptive strategies for network improvement into practice (ML). This will allow the wireless network to create an operational map that is in-depth and accurate of the enormous number of devices that are present in the network [7]. This map can then be used to enhance a number of wireless network-wide tasks, including fault detection and user tracking. In addition features For instance, the use of Cell association, the choice of radio access technologies, beam shaping are just a few of the issues that will be addressed by intelligent resource management tools that will be made possible by ML -guided resource management mechanisms will be able to operate in a fully online manner, in contrast to traditional distributed optimization techniques, which are frequently carried out iteratively in an offline or semi-offline manner ML can be addition to its system-level functionalities.ML tools can be used to reframe problems, as seen in the manner in which coding at the physical layer operates and modulation are planned for the, respectively.inside a general, levels [8][9]. strategy has numerous advantages, as demonstrated by Promises to provide improved robustness and decreased bit error rates. to the obstructions in the wireless channel[10].

It is obvious that ML-based system operation will become a requirement for upcoming wireless networks rather than a luxury. An unfathomably vast range of novel network functions and wireless services will be made possible by machine learning-driven wireless network designs [11]. As confirmed by Huawei's new improvement of insightful portable organizations and Qualcomm's "large innovation house," key ML tools will undoubtedly be used in the sixth generation (6G) of wireless cellular networks. For example, ML capabilities may not be fully supported by 5G networks. Accordingly, the question of whether or not ML tools will be employed in wire in fact stoked demand for an ML-enabled wireless network [12]. These paradigms make use of machine learning (ML) techniques for a variety of tasks, including analyzing user behavior and forecasting it to decide which information to cache and how to pro-actively manage computer resources of utilizing ML for building intelligent wireless networks. Fewer networks have been replaced by that of when such integration will take place [13].

2- Related Work

It is possible to distinguish between exploratory and causal attacks on the reliability of a machine learning system Exploratory attacks are assaults that change a machine learning model's inputs during testing in order to provide incorrect predictions. However, in a causal process data for ML With statistical spam filters, threats into account. In this example, the attack produces avoid detection to spam through or change data to have block valid messages [14][15]. Later, machine learning-based intrusion detection systems were included in the assaults. As an illustration, an attack on a virus detection system could lead to false positives and negatives when classifying network traffic, researchers have found. The system is vulnerable to an allergy attack that causes it to learn signatures that match those created by Biggio and other allergens [16]. Chung and Mok say research assaults against support vector machines using poisoned training data (SVM). Huang et al.'s 2011 review provides of conventional machine learning attack, however none of these techniques take deep neural networks into account the study on adversarial perturbations attacks, which was first presented later confirmed by, is where attacks on deep neural networks first emerged [17][18]. A deep neural network that has been taught to classify input benignly might experience adversarial perturbation, which are subtle changes. In contrast to the backdoor attacks that we investigate in this paper, adversarial perturbation attacks presume neural network was intentionally trained (albeit the test time inputs could have been disrupted) [19].

3. Methodology

Artificial neural network (ANN) is a multi-layer, fully linked network consisting of an input layer, a number of hidden layers and an output layer. Each node in one layer is linked to each node in the layer above it, and by adding more hidden layers, we make the network deeper. In the proposed ANN model, there are three inputs, one output, one hidden layer with ten hidden layer neurons. The structure of the neural network model as shown in Fig. 1.

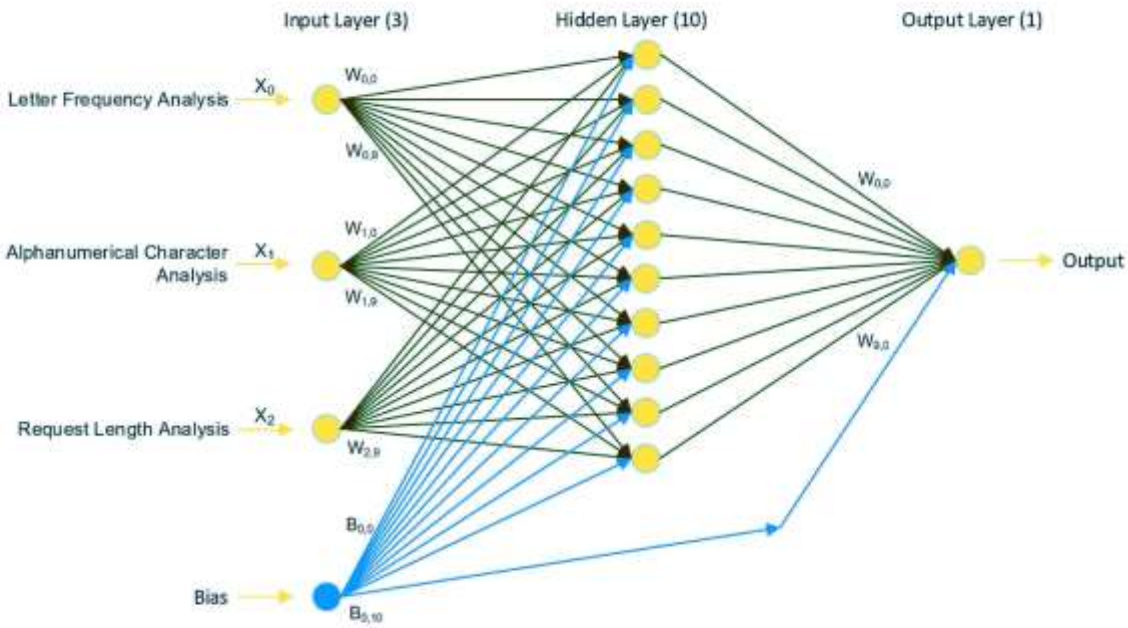


Fig. 1 Proposed artificial neural network model.

The Equation for a particular node looks like this. Its inputs were combined and processed by a nonlinear activation function. When n is the number of inputs for the node, it can be shown as a vector dot product.

$$z = f(x \cdot w) = f\left(\sum_{i=1}^{n} x_i w_i\right)$$

$$x \in d_{1\times n},\ w \in d_{n\times 1},\ z \in d_{1\times 1}$$

I left off the bias word to keep things simple. Bias is an input that each node receives and features are 0, it aids the model's training process. You can safely skip the bias terms if this sounds difficult right now. The above equation, when the bias is taken into account, appears as follows for completeness.

$$z = f(b + x \cdot w) = f\left(b + \sum_{i=1}^{n} x_i w_i\right)$$

$$x \in d_{1\times n},\ w \in d_{n\times 1},\ b \in d_{1\times 1},\ z \in d_{1\times 1}$$

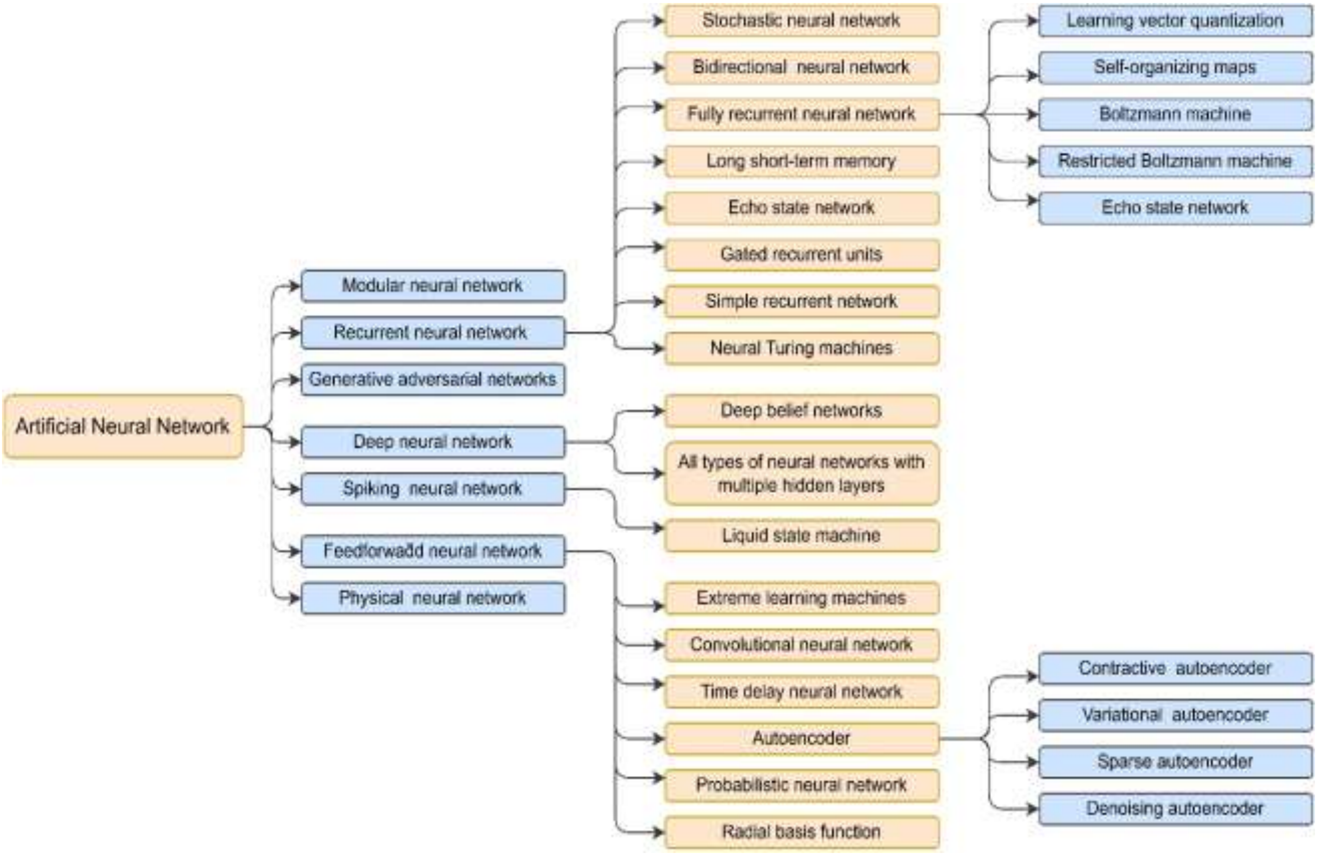
We have only discussed the forward pass up to this point, describes how output is calculated given a weights and inputs. We run the pass to produce the prediction after training is finished. But before our model can truly learn the weights, we must train it. The training process as follows:

- Randomly initialize the weights of each node. There are smart initialization techniques
- Make a forward pass for each training example using the current weights, and determine the outcome of each knot moving from left to right.
- Use the loss function to calculate the error by comparing the final result with the real goal
- Determine the contribution of each weight to the error and use graduated ratios to rebalance the weights. Incorrect gradients must be republished starting from the last layer.

3-1 Preliminaries Of Artificial Neural Networks

The fundamental idea behind machine learning (ML), which emerged from pattern recognition, is that astute robots ought to have the option to gain from and adjust to their current circumstance through experience. There are different kinds of ANNs (see Fig. 2).

Fig. 2 summery of ANN



- A modular neural network (MNN) consists of a number of distinct artificial neural networks (ANN) plus a medium. Each ANN in a MNN is utilized to finish a specific component overall goal that the MNN is trying to achieve. Each ANN output is processed independently to extract the MNN.
- Recurrent Neural Networks (RNNs): These are topologies that provide connections between neurons in different layers. RNNs can be utilized to characterize a number of various structures depending on the communication techniques used in the stochastic neural network.
- Generative adversarial networks (GANs): are composed of two neural networks, one of which determines whether or not the data belongs to a particular class of data type. One neural network is used to train a map from a latent space to a specific data distribution (size, shape, shape).
- Deep neural networks (DNNs) are all ANNs with several hidden layers.
- Spiking neural networks (SSN): These networks are made up of neurons that precisely imitate real brain networks by spiking.
- feedforward neural network (FNN): They are sub-neurons connected to a network by the layers below and above them. Such as extreme learning machines, convolutional neural networks (CNNs), and time delay neural networks.
- physical neural network (PNN): A function of activating the brain using a material with electrically adjustable resistance.

4. Results

The Deep Belief Network and Convolution Neural Network are two effective methods that can be used to utilize deep learning to resolve many challenging issues. Platforms for deep learning can also benefit from while acquiring more sophisticated representations that designed systems often lack. It is obvious that improvements made in the creation of deep machine learning systems will positively influence the future

5. Conclusion:

give a thorough explanation networks with a focus these might applied build generation machine learning. giving an overview of machine learning fundamentals, we go into greater detail into ANNs like very beneficial for. We give an overview of each type's fundamental case illustration. Where relevant. Following that, we go over a variety of wireless applications that can use ANN. Internet of Things system are just a few of these uses. We first identify the main justification for using ANNs while highlighting examples for each application. Then, we discuss the difficulties and possibilities presented usage of in the particular. We then end by outlining prospective future works within each particular area to complement.

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