A Review on Deep Learning Models for Wireless Sensor Networks

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Abstract: ***The sensors in wireless sensor networks gather data about the objects they are used to sense. However, these sensors are limited in their performance by constraints of energy and bandwidth. Deep learning models like LSTM, CNN, RNN and KNN can help in overcoming such constraints. This review surveys deep learning models which have been used to improve the working efficiency of such networks. The emphasis is on applications and this paper also discusses directions for further research work in this area.***

1. Introduction

Wireless sensor networks (WSN) are used to collect data from and make inferences about the environments or objects that they are sensing. WSNs have attracted considerable amount of attention in recent years as shown in figure 1. Research in WSNs area has focused on two separate aspects, namely networking issues [2] such as capacity, delay and routing strategies and application issues [1].

The main feature of wireless sensor networks are self-organizations, multi hop rout, dynamic network topology, node resources limited, data-centric and security problem [3]. Wireless sensor network is a large number of static of mobile sensors node which form the wireless network using self-organization and multi hop method, its purpose is to collaborate detection, processing and transmitting the object monitoring information in areas where the network coverage is possible. The sensor node, sink node, the user node constitutes the three elements of sensor networks. Sensor node is the foundation of the whole network, they are responsible for the perception of data, processing data, store data and transmit data. The sink node are mutual collaboration, node does not directly upload the original data but to use their own processing capacity for proper operation and integration, only forward the data that the lower level node needs. The user node can sense much environmental information including temperature and humidity, pressure, light condition, vehicle movement etc [4][23]. The anticipated applications for WSNs range broadly from homeland security and surveillance to habitat and environmental monitoring[22]. As the demand for these devices increases one cannot expect that the necessary data or domain knowledge will always be available [2][24]. But the main problem that arises here is the accuracy of data may not be upto the level required because there maybe delays due to lacking in the routing capacity. So now the problem of this delay can be rectified to an extent with the help of deep learning models.

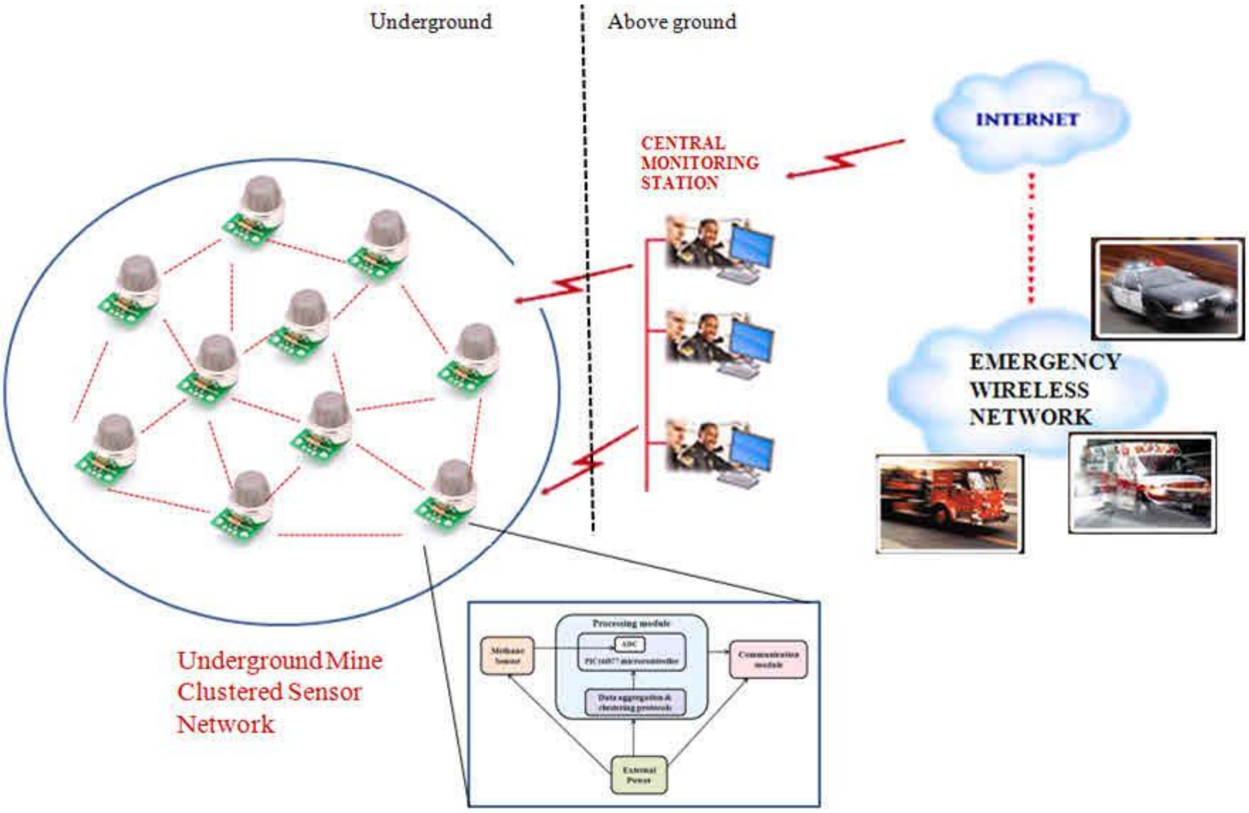

Figure 1: WSN working model

Deep learning is a part of a broader family of machine learning (ML) methods based on learning data representations as opposed to task specific algorithms [22]. Learning can be supervised, semi-supervised or unsupervised [6] [7] [25]. Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bio informatics, drug design, medical image analysis, where it has produced results comparable to and in some cases superior to human experts [8][9][10].

The following two definitions captures the essence of deep learning: [11]

- Use a cascade of multiple layers of non-linear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input.
- Learn in supervised (ex. classification) and/or unsupervised (ex. Pattern analysis) manners.

Applying these definitions to WSNs, we see that the promise of deep learning lies in exploiting historical data to improve the performance of sensor networks on given tasks without the need for reprogramming. More specifically deep learning is important in WSN application for the following main reasons [12][26].

1) Sensor networks usually monitor dynamic environments that change rapidly over time. For example a node's location may change due to soil erosion or sea turbulence. It is desirable to develop sensor networks that can adapt and operate efficiently in such environments [25][]27.
2) WSNs may be used for collecting new knowledge about unreachable, dangerous locations [13] (ex volcano eruption and waste water monitoring) in exploratory applications. Due to the unexpected behavior pattern that may arise in such scenarios, system designers may develop solutions that initially may not operate as expected [28]. System designers would rather have robust deep learning models that are able to calibrate itself to newly acquired knowledge [29] [30].
3) WSNs are usually deployed in complicated environments where researchers cannot build accurate mathematical models to describe the system behavior [28][31]. Mean while some task in WSNs can be prescribed using mathematical models but may still need complex algorithms to solve them [14][32]
4) Sensor network designers often have access to large amount of data but maybe unable to extract important correlations in them [33].

For example in addition to ensuring communication connectivity and energy sustainability, the WSN application often comes with minimum data coverage requirements that have to be fulfilled by limited sensor hardware resources[34]. Deep learning models can then be used to discover important correlations in the sensor data and propose improved senor deployment for maximum data coverage [15][35].

This paper will survey or review the deep learning models like LSTM[36], RNN[37], CNN[38], KNN[38] that would be used in WSN, so that the increasing demand would not be a hinderance in the accuracy and the requirement of hardware does not increase so the cost will also not increase[39].

2. Deep learning in WSN

Deep learning is a type of machine learning that has deeper inner hidden layer cascaded into the network. Its goal is to make machines like computers think and understand as humans thinks by imitating the grid of the human brain connection artificial intelligence (AI) has been investigated in many industries for automation processes such as automated labor, picture and audio detection, decision maker in critical fields and scientific research assistants[40]. Machine learning algorithms are the essential algorithms of AI which extract patterns from raw data to make subjective decisions[16][41]. Machine learning algorithms are subdivided into supervised learning and unsupervised learning. As discussed in section 1 supervised learning algorithm is applied to a dataset that has features and each of those features associated with a label. However, deep learning algorithm comes under unsupervised learning algorithms which are applied to a dataset which has many features in order to learn useful properties from the structure of the dataset.

The training dataset helps the model to learn from the raw dataset and the test dataset helps to validate the output of the model. Deep learning now being used in WSN in different papers and different applications[42]. Long short-term memory (LSTM) units are units of recurrent neural networks (RNN). A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. LSTM was used for wireless sensor networks [17], with results shown for north-south land deformation trend analysis from low cost GPS sensor time series. Convolutional neural network (CNN) a class of deep neural network, most commonly applied to analyzing visual imagery, CNNs uses relatively little preprocessing compared to other image classification algorithms. CNN was used for wireless senor networks in [19][43], with results shown for compressed wireless sensors network images. Recurrent neural network (RNN) a class of artificial neural network where connections between nodes form a directed graph along a sequence. RNNs can use their internal state (memory) to process sequences of inputs. RNN was used for wireless senor networks in [18], where results for the localization of the wireless sensor networks was studied using RNN. K- nearest neighbors (K-NN) is a non-parametric method used for classification and regression. In both cases, the input consists of the K closest training examples in the feature space. The output depends on whether K-NN is used for classification or regression. KNN was for missing data estimation in wireless sensor networks in [20]. Various papers and researchers have explained in detail that how these four deep learning modelsLSTM, CNN, RNN and KNN can be used in wireless sensor networks.

3. Deep learning models in WSN

The data collected from wireless sensor network indicate the system status, the environment status or the health condition of human being and it can use the WSN data to carry out appropriate work by processing it. Now we will see that how the four deep learning models LSTM, CNN, RNN and KNN can be fruitfully applicable to WSN.

3.1 Long short term memory (LSTM) in WSN

In theory, classic (or "vanilla") RNNs can keep track of arbitrary long-term dependencies in the input sequences. The problem of vanilla RNNs is computational (or practical) in nature: when training a vanilla RNN using back-propagation, the gradients which are back-propagated can "vanish" (that is, they can tend to zero) or "explode" (that is, they can tend to infinity), because of the computations involved in the process, which use finite-precision numbers. RNNs using LSTM units partially solve the vanishing gradient problem, because LSTM units allow gradients to also flow unchanged. However, LSTM networks can still suffer from the exploding gradient problem.

There are several architectures of LSTM units. A common architecture is composed of a cell (the memory part of the LSTM unit) and three "regulators", usually called gates, of the flow of information inside the LSTM unit: an input gate, an output gate and a forget gate. Some variations of the LSTM unit do not have one or more of these gates or maybe have other gates. For example, gated recurrent units (GRUs) do not have an output gate.

Intuitively, the cell is responsible for keeping track of the dependencies between the elements in the input sequence. The input gate controls the extent to which a new value flows into the cell, the forget gate controls the extent to which a value remains in the cell and the output gate controls the extent to which the value in the cell is used to compute the output activation of the LSTM unit. The activation function of the LSTM gates is often the logistic function.

There are connections into and out of the LSTM gates, a few of which are recurrent. The weights of these connections, which need to be learned during training, determine how the gates operate. LSTM is a special type of RNN which is efficient in learning long term dependencies. The block diagram of a basic version of a LSTM cell is presented in figure 2 along with the corresponding equations (1-6) [21].

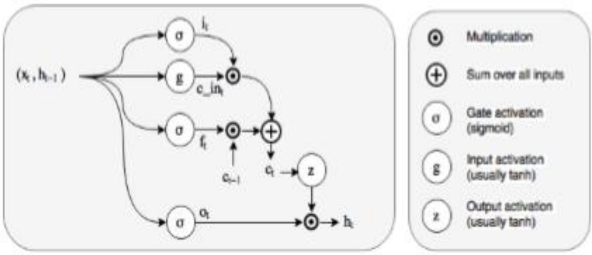

Figure 2: LSTM cell used used in the hidden layers of the model

- Gates

it = σ(Wxixt + Whiht−1 + bi) input gate's activation vector…(1)
ft = σ(Wxfxt + Whfht−1 + bf)forget gate's activation vector…(2)
ot = σ(Wxoxt + Whoht−1 + bo) output gate's activation vector (3)

- Input transform

c int = tanh(Wxcxt + Whcht−1 + bc in) …(4)

- State update

ct = ft ·ct−1 + it ·c int cell state vector …(5)
ht = ot ·tanh(ct) hidden state vector also known as output vector of the LSTM unit …(6)

LSTM cells have an internal state or memory (ct) along with three gates namely input date (it), forget gate (ft) and output gate (ft). Based on the previous state and the input data the cells can learn the gate weights for the specified problem. This gating mechanism helps LSTM cells to store information for longer duration thereby enabling persistent feature learning [17].

Using the above mentioned concepts of LSTM are used to model a sensor node, the node's dynamics, and interconnections with other sensor network nodes. A neural network (NN) modelling approach is used for sensor node identification and fault detection in WSNs.

3.2 Convolutional neural network (CNN) in WSN

Many wireless sensor networks require a classification of the incoming data as a way for domain scientists to better understand the collected data, or with the purpose of performing different types of actuation in the environment and this can be done with the help of a deep learning model know as CNN.

The use of CNN in WSN can be further explained with the help of figure 3 which illustrates the flow of our system as two different pipeline phases. As the figure 3 shows, a level of human interaction is required to provide the ground truth for training the CNN model. With this (compressed) data, domain scientist can label the data on the backend server prior to training the CNN model. This is a human involved process that cannot be in training the deep learning models. We agree that it may be more accurate for domain scientist to label uncompressed original data rather than the compressed data but compression improves efficiency (ex: use less energy/bandwidth resources) [19].

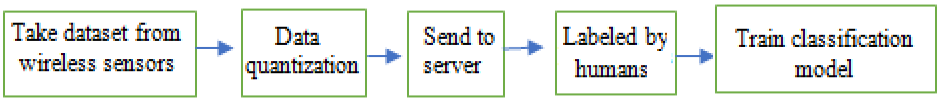

Figure 3: System pipeline for model training using CNN

3.3 Recurrent neural network (RNN) in WSN

A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a sequence. This allows it to exhibit temporal dynamic behavior for a time sequence. Unlike feedforward neural networks, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition.

The term "recurrent neural network" is used indiscriminately to refer to two broad classes of networks with a similar general structure, where one is finite impulse and the other is infinite impulse. Both classes of networks exhibit temporal dynamic behavior. A finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced with a strictly feedforward neural network, while an infinite impulse recurrent network is a directed cyclic graph that can not be unrolled.

Both finite impulse and infinite impulse recurrent networks can have additional stored state, and the storage can be under direct control by the neural network. The storage can also be replaced by another network or graph, if that incorporates time delays or has feedback loops. Such controlled states are referred to as gated state or gated memory, and are part of long short-term memory networks (LSTMs) and gated recurrent units.

WSN consists of a large number of sensors, which in turn have their own dynamics. They interact with each other and the base station, which controls the network. In multi hop wireless sensor networks, information hops from one node to another and finally to the network gateway or base station. RNN consists of a set of dynamic nodes that provide internal feedback to their own inputs. They can be used simulate and model dynamic systems such a network of sensors [5]. RNNs are used to model a sensor node, the node's dynamics and the interconnections with other sensor network nodes. A neural network modelling approach is used for sensor node identification and fault detection in WSNs. The input to the neural network is chosen to include previous output samples of the modelling sensor nodes identification and fault detection in WSNs [18]

3.4 K-nearest neighbor (K-NN) in WSN

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms [44].

Both for classification and regression, a useful technique can be used to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor [45].

The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required. A peculiarity of the k-NN algorithm is that it is sensitive to the local structure of the data as shown in figure 4.

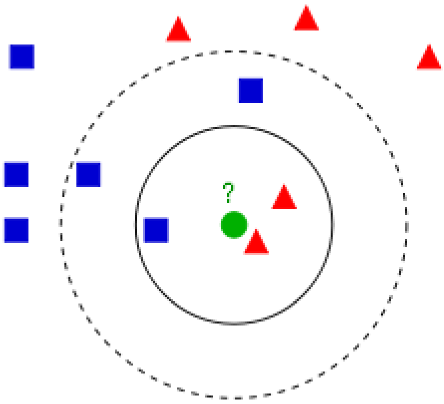

Figure 4: Example of KNN classification

The K-NN method proposed by Fix and Hodges that was considered of the non-parametric methods used for classification of new object based on training samples and attributes. The KNN is considered a supervised learning algorithm that a new instance query result in classified based on KNN category. The advantage of KNN is ease to implement and simple. KNN is not negatively affected when training data are large and indifferent to noisy training data and these are the soul reason why KNN would be very successful and helpful when used in WSN as there are a number of nodes which provide data and to take the data of the most accurate node to increase the efficiency [46]. There is a need to determine parameter K and calculate the distances between the query instance and all the training samples, sort the distances and determine the nearest neighbors based on the Kth minimum distance, additionally determine categories of the nearest neighbors [20] [21].

4. Future Direction

Deep learning based information processing in WSN is at an entering stage, as compared to machine learning traditional algorithms and WSN. Currently researches mainly focus on applying deep learning techniques to solve particular problems like efficiency, energy management, accuracy etc in WSN. Different researchers will have different assumptions, application scenarios and preferences in applying deep learning models [48]. These differences represent a major challenge in allowing researchers to build upon each other's work so that research results will accumulate in the community. Thus a common architecture across the WSN deep learning community would be necessary [47].

Moreover there is a very good scope of applying semi supervised models on WSN which is not yet been researched to its full extent till date. This paper points out the applicability of deep learning and few of its models on the WSN [49].

5. Conclusion

This article surveys the deep learning models applied in WSN from the application perspectives. Deep learning techniques have been applied in solving problems such as energy-aware communication, optimal sensor deployment and localization, resource allocation and task scheduling in WSN [50]. So all in all this is a great way ahead for the researchers in the future.

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