Improved Wireless Communication System Based on Deep Neural Network and Classification Techniques

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ABSTRACT

The rapid uptake of mobile devices and the rising Popularity of mobile applications and services pose unprecedented demands on mobile and wireless networking infrastructure. Upcoming 5G systems are evolving to support exploding mobile traffic volumes, real-time extraction of fine-grained analytics, and agile management of network resources, so as to maximize user experience. In this paper we resent deep neural network with support vector machine classifier and improve the performance of channel boosting in the terms of bit error rate and block error rate, Our simulated result shows better results than the previous techniques.

Keywords:- Wireless sensor network, Deep learning, Support vector machines, Bit error rate, Block error rate, internet of Things.

INRODUCTION

Internet connected mobile devices are penetrating every aspect of individuals' life, work, and entertainment. The increasing number of smart phones and the emergence of evermore diverse applications trigger a surge in mobile data traffic.

Indeed, the latest industry forecasts indicate that the annual worldwide IP traffic consumption will reach 3.3 zetta bytes by 2021, with smart phone traffic exceeding PC traffic by the same year. Given the shift in user preference towards wireless connectivity, current mobile infrastructure faces great capacity demands. In response to this increasing demand, early efforts propose to agilely provision resources and tackle mobility management distributively. In the long run, however, Internet Service Providers (ISPs) must develop intelligent heterogeneous architectures and tools that can spawn the 5th generation of mobile systems (5G) and gradually meet more stringent end-user application requirements.

Meanwhile, the rise of the Internet of Things (IoT) also contributes a large portion of connected devices and data traffic, accompanied with diverse types of connectivity technologies, such as Bluetooth Low Energy, Zigbee, Low Power Wide Area Networks, and narrowband IoT. These heterogeneous IoT devices are expected to be supported by 5G networks in a massive scale, which provide a seamless connectivity of these heterogeneous components.

Network services become ever more sophisticated, real-time dependent and diversified. During the early phase of network services and infrastructure exponential expansion, it was almost "all about the wire", meaning that during installation and maintenance phases of network lifecycle, most of the issues to deal with were predominantly related to lower protocol stack layers -the physical and the link one , Medium Access Control (MAC) in particular. However, as the related technologies-primarily light wave and wireless-mature, protocol stacks become more complicated in higher layers, with even wider "horizontal dispersion" of protocols, as coming out of demands of contemporary multiservice and multiprotocol networks.

In recent years, deep learning has garnered tremendous success in a variety of application domains. This new field of machine learning has been growing rapidly and has been applied to most traditional application domains, as well as some new areas that present more opportunities. Different methods have been proposed based on different categories of learning, including supervised, semi-supervised, and un-supervised learning. Experimental results show state-of-the-art performance using deep learning when compared to traditional machine learning approaches in the fields of image processing, computer vision, speech recognition, machine translation, art, medical imaging, channel selection, medical information processing, robotics and control, bioinformatics, natural language processing, cyber security, and many others.

We begin with a brief introduction to deep learning, highlighting the basic principles behind computation techniques in this field, as well as key advantages that lead to their success. Deep learning is essentially a sub-branch of ML, which essentially enables an algorithm to make predictions, classifications, or decisions based on data, without being explicitly programmed. Classic examples include linear regression, the k-nearest neighbors classifier, and Q-learning. In contrast to traditional ML tools that rely heavily on features defined by domain experts, deep learning algorithms hierarchically extract knowledge from raw data through multiple layers of nonlinear processing units, in order to make predictions or take actions according to some target objective.

II DEEP NEURAL NETWORKS

Deep neural networks (DNNs) are considered suitable for tackling complex learning problems. The multiple processing layers of deep architectures provide the advantage of devising multiple mapping functions for complex problems. This inherent ability has made DNNs to be one of the best tools in pattern recognition. DNNs especially, convolutional neural networks (CNNs), have shown exemplary performance on complex learning problems. CNNs are considered as effective learning models that have achieved impressive results on challenging tasks of object detection, image recognition, classification, and retrieval, etc. The high learning ability of a CNN is mainly due to two of its characteristic features; firstly, CNN learns representation in a hierarchical manner that helps to untangle complexities and learn generic representation from data. Secondly, with the increase in depth, the use of multiple mapping functions helps in handling hundreds of categories' recognition task. Moreover, high-level features can be reassigned for generic recognition tasks with no additional fine-tuning (a concept is known as multitasking). The use of a 2D convolution operator in CNN has the potential to provide effective representations of the original image. This characteristic of CNN has strengthened its ability to directly recognize the patterns from raw pixels with diminutive or no preprocessing.

Deep learning approaches can be categorized as follows: Supervised, semi-supervised or partially supervised, and unsupervised. In addition, there is another category of learning approach called Reinforcement Learning (RL) orDeepRL (DRL)which are often discussed under the scope of semi-supervised or sometimes under unsupervised learning approaches. Below figure shows the pictorial diagram.

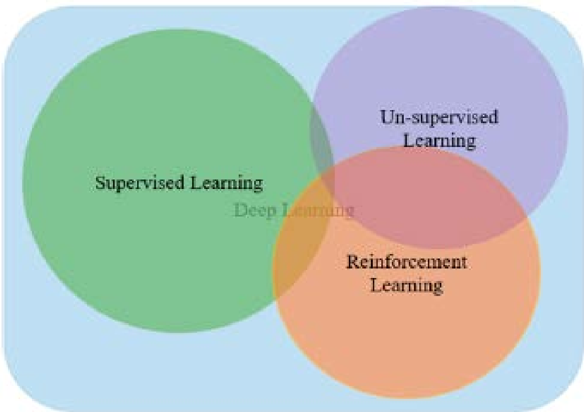

Fig 1. Category of Deep Leaning approaches.

III PROPOSED WORK

We present a novel architectural enhancement of "Channel Boosting" in a deep convolutional neural network (CNN). This idea of "Channel Boosting" exploits both the channel dimension of CNN (learning from multiple input channels) and SVM (Support vector machines).

Support Vector Machines (SVM) often outperform other machine learning methods, However, the standard SVM has a single adjustable layer of weights and Instead of using such "shallow models", deep architectures can be better alternatives. SVMs use a-priori chosen kernel functions to compute similarities between input vectors, Therefore we propose the deep SVM (DSVM), The DSVM contains multiple layers of SVMs. More SVMs can be used to create larger feature Representations, All support vector coefficients (ᾱ-values) are trained using gradient ascent or descent on an adapted dual objective function. Just like Multi-layer perceptrons consist of simple perceptrons, the DSVM consists of SVMs.

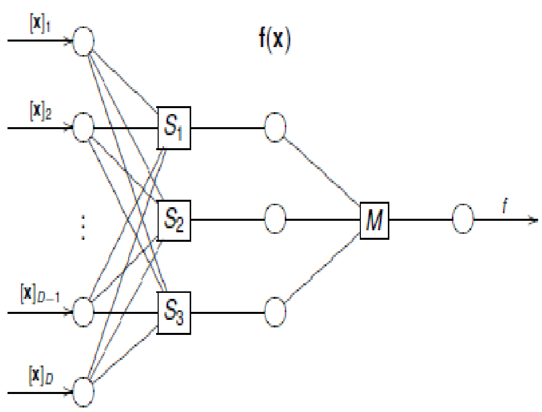

Fig 2. Support vector machine architecture.

Where,
Input layer of size D.
Total of d SVMs Sa, each one extracting one feature Central feature layer of size d.
Main support vector machine M.

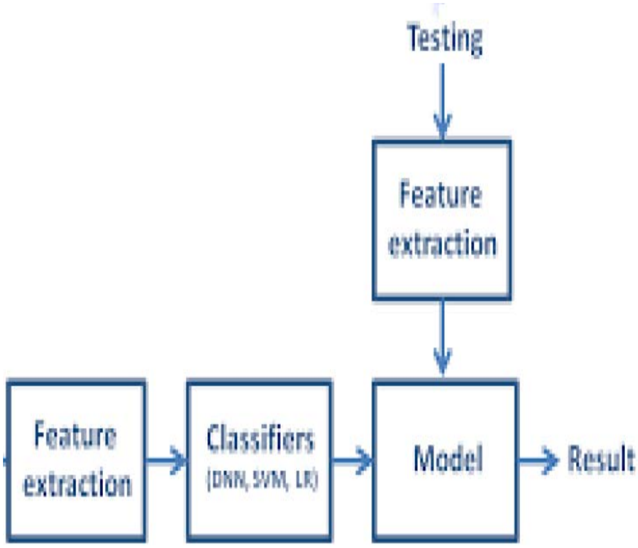

Fig 3. Proposed method block diagram.

IV EXPERIMENTAL RESULT ANALYSIS

The fifth generation (5G) of wireless communication networks will be inundated with large numbers of users with heterogeneous demands of data rates, delay, and energy efficiency. To meet these demands, small-cell densification in heterogeneous networks (HetNets) is a key solution for 5G networks, offering increased capacity with spectrum reuse between macro-cell base stations (MBSs) and small-cell base stations (SBSs). To support flexible SBS deployments, wireless backhauling from a nearby MBS is an attractive alternative to traditional wired solutions.

Bit Error Ratio (BER) and Block Error Ratio (BLER) are important QoS parameters in wireless networks, but BER is no good indicator of BLER and vice versa. With this respect, although the 3G (UMTS) systems performance is still described in terms of both BER and BLER, with LTE, exclusively BLER (effectively the sub-frame error rate), is used. Further-more, as at higher protocol layers, data blocks pertain to relevant protocol data units (PDU) frames and packets at Link Layer and Network Layer, respectively, the layer-specific

BLER is accordingly and commonly referred to as Frame Error Ratio (FER) and Packet Error Ratio (PER), respectively. Specifically, with LTE, BLER is regarded as the count of exhibited negative link-layer protocol acknowledgements, relative to the total count of acknowledgements. However, such BLER estimation scheme heavily depends on the success rate of negative acknowledgements transport via return channel, and so does not deliver trustworthy low values, which are requested by higher protocols (mostly TCP). Therefore, BER and/or the Symbol Error Ratio (SER) are and will certainly continue to be used by network equipment manufacturers during tests in research and development as well as in production.

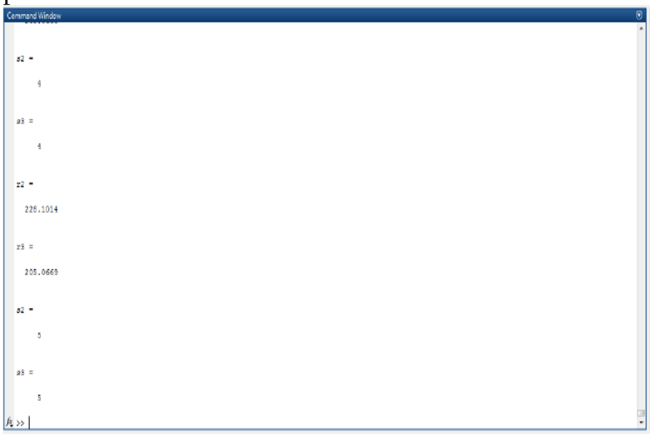

Fig 4. Experimental procedure of simulated proposed work.

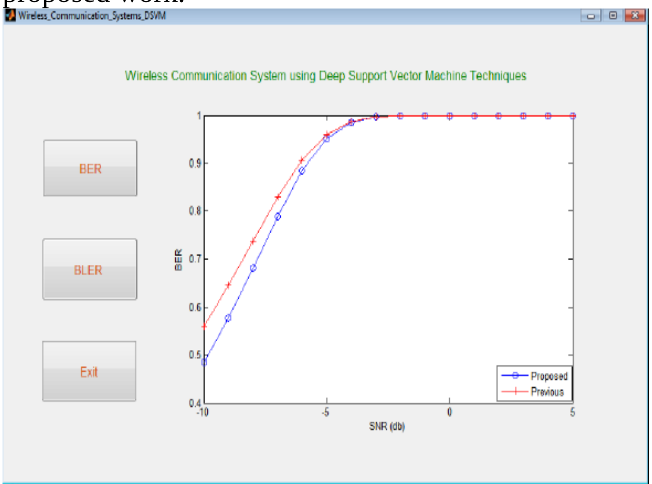

Fig 5. Comparative experimental procedure of previous and proposed work.

V CONCLUSION

Channel encoding and decoding are important components in modern communication systems. The research about deep learning application for physical layer has been received much attention in recent years. In this paper, we propose a Deep Learning (DL) and Support vector machines (SVM) based channel Estimator. In this work, we propose a novel idea of "Channel Boosting" to improve deep neural networks' with support vector machines. We have demonstrated that the use of Channel Boosted input can improve the performance of a deep SVM.

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