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The Effectiveness of Using Deep Learning Algorithms in Predicting Daily Activities

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ABSTRACT

Predicting Activities of Daily Living (ADL) for elder people could let them live actively, independently and healthy. In this paper, Authors perform a comparative study to address the effectiveness of deep learning algorithms on ADL. As a baseline structure, The Convolutional Neural Networks (CNN's) as a deep learning algorithm is employed to perform the experiments and conducting the comparative study with the very common used traditional machine learning algorithms. Several factors in the CNN are manipulated to gain the best result in predicting the ADL in comparison with the most ML result in this matter. To reduce the threat to validity, very common data set are used in several previous studies in term of ADL prediction is adopted in this paper. The dataset was collected from a wearable chest accelerometer. The total numbers of participants are 15 and they were performing 7 main activities namely standing up, working at the computer, going up downstairs, standing, walking, walking and talking with someone and talking while standing, walking and going up downstairs. Three experiments were conducted in this paper, and CNN provides promising result in term of ADL predictions for the very common data set in this field and ML algorithms.

Key words: Machine Learning, Classification, Pattern Recognition, Activity Recognition, ADL, deep learning algorithms.

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1. INTRODUCTION

Elder people can be more susceptible to life accident and many diseases such as Osteoarthritis, diabetes and other diseases. Many healthcare companies aim to provide several mechanisms to help elder people by supporting them to do all daily living activities in easy way. Although, the daily activities of elder people are known, health care services and researchers address and investigate their daily living activities. In which inclusive perception of ADL could lead to grasping their requirements and mitigate the challenges that they face through their lives.

The competence to automatically infer and monitor infer human actions in naturalistic environments is fundamental for many applications in wide range of areas such as energy management, context-aware personal assistance and healthcare. Latterly, wearable cameras such as the GoPro 1 and Narrative 2 enable capturing human actions and behaviors [1]. Deep learning algorithms allow computational models to learn data representations with various levels of abstraction. These methods can dramatically improve the state of the art in speech recognition, object detection, object recognition, and many other domains like drug discovery and genomics. Deep learning detect complicated structure in large datasets by using the backpropagation algorithms to determine how a machine change its internal parameters that are used to compute data representation in each layer from the data representation in the previous layer. Deep convolutional nets have brought about breakthroughs in image processing, whereas recurrent nets have shown light on sequential data such as speech and text [12].

The goal of this work is to evaluate and compare the efficiency of deep learning algorithms in classifying and predicting collected dataset of ADL data from a wearable accelerometer. The comparison is conducted against very well-known Machine learning algorithms using the same data set.

Section II summarizes some related works, Section III presents deep learning algorithms that are used in this study, Section IV describes the research methodology, and Section V concludes the paper.

2. RELATED WORK

Activities of Daily Living are the activities that people perform during their day, such as showering, wearing, eating working and other activities [2]. Authors in [3] Studied the effectiveness of machine learning algorithms on Activities of Daily Living dataset, the aim of their study is to detect the potential of understanding how Machine learning algorithms could deal with Activities of Daily Living data in terms of analyzing, predicting, and understanding and clustering the Activities of Daily Living activities. A surveillance system was developed to analyze people body posture when the recorded video data is not sufficient, and to show how the event detection performance enhances the system [4].

Latterly, activity recognition devices are extensively used across a wide variety of environments. The expansion of activity recognition encourages many researchers to focus on the feasibility of monitoring activity recognition to propose the potentiality for the elder people to be engaged in the environment of their diseases [5].

Daily activities can be detected within accuracy rate by using a single triaxial accelerometer, except mouth movements activities, authors also found that activity recognition based on combining classifiers outperform the activity recognition based on the single accelerometer [6].

Akour et al. [7] addressed the capability of the ensemble machine learning algorithms to outperform the effectiveness of 5 base-level classifiers in terms of predicting daily living activities. The dataset was collected from a wearable accelerometer mounted on the chest of 15 participants performing seven activities. The results were evaluated using precision, recall, and F-measure.

Two predictive models were developed in [8] to predict the type of activity; the wrist accelerometer got an average accuracy of 87%, while hip accelerometer got an average accuracy of 92%.

A study show that integrating automatically learned features, handcrafted features, and Random Forest for activity recognition is effective in activity recognition and it can be adapted into wide range of environments [9].

Authors in [10] presented a hierarchical model to recognize complex activities, complex activities were generated by using a clustering algorithm to improve the performance of complex activity recognition. The experimental results show that the developed method has the capability to recognize complex activities effectively and efficiently.

Another research in the field of activity recognition was developed by using a smartphones in activity recognition, the collected data employed to recognize human physical activities and by using classification method called MCODE, results show that MCODE is serviceable to recognize physical activities using smartphone accelerometers [11].

3. DEEP LEARNING ALGORITHMS

Deep Learning algorithms extract complex high-level abstractions as data representations via a hierarchical learning process. The main benefit of Deep Learning is learning and analysis of huge amounts of unsupervised data, making it a worthy tool for Big Data Analytics where data is uncategorized and unlabeled. In [22] authors represented a study to investigate how deep learning algorithms can be employed to address the challenges in field of big data analytics, extracting complex patterns from huge volumes of data, data tagging semantic indexing, and simplifying discriminative tasks. Moreover, they studied some Deep Learning aspects.

Convolutional Neural Networks (CNN's) consists of pooling and convolutional layers followed by one or more fully connected layers, these layers are accumulated on top of each other's to form a deep model. Convolutional Layers learn the feature representations of their input. The neurons are coordinated into feature maps. Each neuron in a feature map is linked to a neighborhood neuron in the previous layer via a set of trainable weights, occasionally used as a filter bank[12].

Convolutional Neural Networks (CNN's) is One type of neural network that is able of extracting information out of the image, data containing spatial information, etc.. CNN's are feed-forward networks in that information flow from their inputs to their outputs takes place in one direction only [13]. CNN's considers as one of the main models for extracting features from the text data, audio, and video. They have proved tremendously successfulness in practical applications [14].

The importance of building accurate prediction models is to captures the syntax and semantics of source code. In [15] Convolutional Neural Network (DP-CNN) proposed Defect Prediction model. CNN is employed to automatically learn semantic and structural features of programs. The developed approach consists of four phases, starting with Abstract Syntax Trees (ASTs) which is used to extract tokens that are encoded into numerical vectors. Then it utilizes CNN and integrates it with traditional defect prediction features. In the final phase, it uses the Logistic Regression to determine if the code files contain buggies or not.

Deep learning can be used as preliminary process in software fault prediction. In [16] a pre-training technique is used for a shallow ANN. A Denoising AutoEncoder (DAE) is used for this purpose. The model begins the training process from the weights and bias of a trained DAE. The execution of experiment is conducted on NASA datasets. The suggested model (Pre-ANN) was compared with SVM, ANN, Principal Component Analysis (PCA)-SVM, Kernel PCA-SVM and AE-SVM. Results show that the pre-training process improves the accuracy. It achieved higher accuracy in four dataset out of seven dataset. Authors in [23] provide an overview of different text emotion recognition methods for extracting text features, where diverse classifier algorithms are discussed and used.

4. RESEARCH METHODOLOGY

In this paper, authors were keen to study the effectiveness of deep learning algorithm in predicting ADL. In order to make the research results are noticeable and add contribution to the body of the art, a comparative study is conducted with latest result that has been achieved by Akour et al. [7]. In their study, the selected base learner's performances are compared with ensemble methods for predicting ADL. The studied base learners were Bayesian Network, Optimization, Naïve Bayes, Decision Table, Sequential Minimal and J48 and the selected ensemble learners are bagging, decorate, boosting and random forest.

4.1 Model Tuning

Variant parameters might be altered during each experiment, to examine their influence on accuracy. Tuning the parameter is can play and crucial role in articulating the correct settings to obtain desired results. Although there is no fixed rules to follow in setting these parameters, in general, still the choice is relies on the type and size of the training dataset. Choosing correct settings is essential but consider as complex part for network training. However, tuning parameter is mainly depends on experience rather than theoretical knowledge. Trade-offs is intrinsic in the parameter selection due to the restrictions such as memory limitation [17]. Figure 1 shows the major steps of the research methodology.

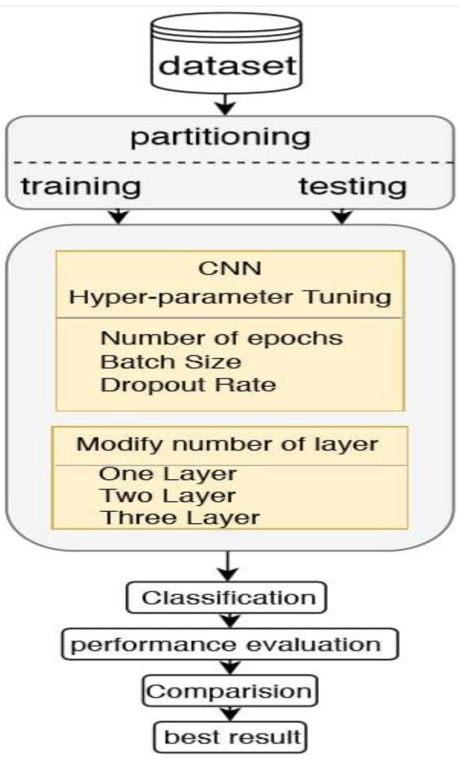

Figure 1: Research Methodology Steps

The main parameter tuning settings are listed below:
Number of epochs: an epoch is the number of passes through the data set. It encompass one forward and backward pass during training [17]. Usually, the neural networks must be trained on various epochs in order to have satisfied results. Number of epoch represents the training iteration number, while the number of training sample is the number training iterations batch size. The size of the training set and the size of the network are directly determined the duration for each epoch. There is no restriction on the number of epochs. Authors conducted three main experiments and the number of epochs is changed until the best results are reached.
Batch size: is the number of training samples that is used in one epoch and will be propagated through the network. Batch size is used to control many predictions that must be made at a time, and fit the model. In general, the larger batch size required more memory space [18]. However, we can improve scalability and efficiency of the computational by providing more data-parallelism. On other hand, small batch sizes are preferable since they head to produce convergence in small number of epochs [19]. In this study, the experiments utilized different batch sizes from 1 up to 20.
Finally, the last parameter that might influence greatly the performance of the networks is number of hidden layers, neurons in the hidden layer. The number of layers becomes the most important criterion in the architecture of the networks [20]. In this study, authors tried to optimize the accuracy by reaching the best number of layers from various iterations from 1 to 3. Jay Robert and Del Rosario performed several experiments in the field of Face Recognition by employing Deep Convolutional Neural Network for prediction purposes. Their system use 3 main cameras to collect the data set in a Multi view Vision Environment, and then they applied the dee learning algorithm to predict the matched faces.

4.2 Data Set

The dataset gathered data from a wearable chest accelerometer. The dataset is collected specifically for ADL research purposes [21]. Uncalibrated Accelerometer Data are collected from 15 participants performing 7 activities. The dataset provides challenges for identification and authentication of people using motion patterns. The main activities in this data set are: going up downstairs, standing, walking, walking and talking with someone and talking while standing, walking and going up downstairs. The data set consist of 102340 instances.

5. RESULT AND DISCUSSION

As mentioned previously, the comparative study will be conducted in this paper with very recent result that has been achieved by Akour et al. [7] in field of ADL prediction. Table 1 shows the comparative results of Akour et al. [7] of applying the ensemble approaches against the base-level classifiers in terms of F-measure.

Table 1: The base level and meta-level Classifications Results in terms of F-measure (Akour et al. [7])

	Base	Boosting	Bagging	Decorate	Rotation Forest
Naïve Bayes	0.772	0.772	0.774	0.772	0.769
Bayes Net	0.817	0.817	0.821	0.817	0.823
SMO	0.686	0.686	0.687	0.686	0.687
Decision Table	0.785	0.807	0.789	0.789	0.804
J48	0.827	0.814	0.829	0.798	0.841

Akour et al. [7] state that, the base learners experiments showed that J48 achieved the best using the studied dataset while SMO was the worst performing model. While the results of ensemble learner's experiments showed that Boosting using decision table as the base classifier achieved the best improvement over base learners. In addition, the Bagging approach was able to predict five activities out of seven more efficiently than the other approaches while the rotation forest approach was able to predict the remaining two activities more efficiently than the rest.

In this paper, Recall, Precision, Accuracy and F-measures are calculated to perform comprehensive comparative study.

Three experiments are performed and the studied measures are collected. The three factors (i.e. # of layer, epoch, and batch size) are manipulated until the experiments achieve the best result. The best batch size was 15, the best epoch was 20, while the best number of layer was 1. The CNN outperforms the base learners algorithms in the three experiments although the experiment number three achieved the lowest result in comparison with the experiment number 1 and 2, still CNN reveal the best prediction performance in the field of ADL prediction as shown in table 2.

Table 2: CNN and Base learner's comparative results (Akour et al. [7])

	Accuracy	**Precision**	**Recall**	**F-measure**
Naive Bayes	0.774	0.755	0.811	0.772
Bayes Net	0.823	0.815	0.832	0.817
SMO	0.687	0.640	0.738	0.686
Decision Table	0.807	0.770	0.812	0.785
J48	0.841	0.823	0.840	0.827
CNN's Results				
1-layer	0.999941	0.999941	0.999941	0.999941
2- layer	0.999911	0.999911	0.999911	0.999911
3- layer	0.9781770	0.978064	0.9781770	0.974149

In other side, figure 2 shows the result of the CNN in comparison with the ensemble methods in terms of F-measure.

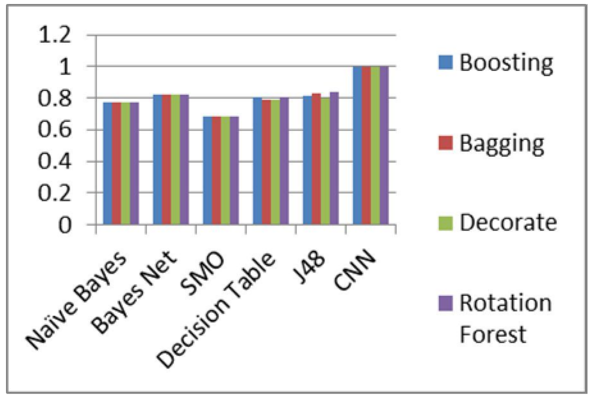

Figure 2: CNN and ensemble methods comparison

As shown in figure 2, the highest F-Measure is achieved by CNN against all studied ensemble methods in Akour et al. [7] study. CNN provides promising result in term of ADL predictions for the very common data set and ML algorithms.

6.CONCLUSION AND FUTURE WORKS

This work aims to address the effectiveness of deep learning algorithm on the accuracy of user movement prediction. A well-known benchmark dataset selected from the UC Irvine Machine Learning Repository is used for evaluation. CNN is used and set of factors manipulation are conducted to achieve the best result. To strengthen the result, authors perform a comparative study with very recent result of ML in the ADL predictions. The CNN reveals very promising result in predicting the ADL in terms of Recall and F-measurements. As future works, authors will study other deep learning algorithms and compare the result with the CNN result. Another contribution can be achieved by considering large scale data set.

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