Performance Analysis of Data Fusion Methods Applied to Epileptic Seizure Recognition

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Abstract

Epilepsy is a chronic neurological disorder that is caused by unprovoked recurrent seizures. The most commonly used tool for the diagnosis of epilepsy is the electroencephalogram (EEG) whereby the electrical activity of the brain is measured. In order to prevent potential risks, the patients have to be monitored as to detect an epileptic episode early on and to provide prevention measures. Many different research studies have used a combination of time and frequency features for the automatic recognition of epileptic seizures. In this paper, two fusion methods are compared. The first is based on an ensemble method and the second uses the Choquet fuzzy integral method. In particular, three different machine learning approaches namely RNN, ML and DNN are used as inputs for the ensemble method and the Choquet fuzzy integral fusion method. Evaluation measures such as confusion matrix, AUC and accuracy are compared as well as MSE and RMSE are provided. The results show that the Choquet fuzzy integral fusion method outperforms the ensemble method as well as other state-of-the-art classification methods.

1 Introduction

Epilepsy is a very common neurological disorder, which affects one in every 100 persons worldwide [1]. When a person has an epileptic episode then paroxysmal abnormal ultra-synchronized electrical activity can be measured in the brain, which usually occurs suddenly. Researchers are looking for an automated way to monitor and detect an epileptic episode such that the patient and neurologist can be warned early on in order to prevent potential risks to the patient [2]. However, one of the challenges is that the time frequencies of epileptic episodes are uncertain, and thus are not easy to detect.

Researchers have used sensors [3] to collect biological data from the patients' surface via electrocardiogram (ECG), electromyography (EMG) [4], motion data [5], and electrodermography (EDG) [6]. The sensors are usually integrated into clothing such as E-textiles [7], capacitive sensing [8], polymer materials, such as carbon nanotube (CNT)-polydimethylsiloxane (PDMS) [9], Ag/AgCl electrodes [10], and microneedle arrays [11]. The advantage of the so-called wearable sensor systems is that they can non-invasively monitor the signals of epileptic patients also for long periods. However, measuring brain signals can provide faster and more usable information.

Thus, many researchers have looked at different approaches to directly measure 'epilepsy signals' from the brain. These are positron emission tomography (PET), single photon emission computed tomography (SPECT), magnetic resonance imaging (MRI), and functional magnetic resonance imaging (fMRI) [12]. At the moment, most research investigations make use of video-electroencephalograms (EEGs) [13, 14]. EEGs provide temporal information but also spatial information of the electrical activity in the brain. The video-EEG technique is seen as the current best approach to study epilepsy. Since the physiological processes of a seizure are typically non-stationary, dynamic, and nonlinear, the differentiation of rhythmic discharges from non-stationary processes provides challenges to the analysis of the EEG signals.

The automated way to detect EEG signals includes the two tasks, namely feature extraction and classification. The extracted features can be divided into four categories:

- Statistical features
- Fractal dimension features
- Entropy features
- Time-frequency domain features

Many different research studies have used a combination of time and frequency features for the automatic recognition of epileptic seizures. The classification task to automatically detect EEG uses machine learning approaches mostly driven in the supervised learning mode.

In this paper, the 5-class epileptic seizure recognition data set is investigated. Multi-label classification is a challenging task and is usually being done using ensemble methods in order to achieve the best classification performance. State-of-the-art multi-label learning approaches explain the label correlations in order to improve the accuracy of the learner by building an individual multi-label learner or a combination of learners that are based on a group of single-label learners. Moreover, it is well-known that ensemble learning can improve the generalizability ability of the learning system by using multiple base learner, and thus, improving the accuracy as well as the diversity of the base learners [15]. Therefore, this investigation compares the ensemble method with the Choquet fuzzy integral fusion method, which has shown very promising results in the past. Three different machine learning algorithms are used namely RNN, ML and DNN as the input for the two different fusion methods (ensemble and Choquet fuzzy integral fusion).

2 Related Work

Related work mostly concentrates on the Bonn datasets [16]. For example, in [17] a neural network (NN) classification technique was applied in the field of brain science. Support vector machines (SVMs) was used to identify the EEG signals of epilepsy patients obtaining good recognition performance [18], [19], [14]. A least squares support vector machine (LS-SVM) to classify two-class seizure and non-seizure EEG signals was proposed in [20] reporting a 98.0-99.5% accuracy using a radial basis function (RBF) kernel, and a 99.5-100% accuracy using a Morlet kernel.

Another approach used an Ada-Boost classifier to achieve good accuracy for spike detection of epileptic seizures [21]. Given the no-free-lunch theorem [22], several classification algorithms have been applied to seizure detection, including random forests (RF), K-nearest neighbors (KNN) [23], and Bayesian neural networks [24]. All these approaches yielded classification results ranging from 93% to 99.66% in terms of accuracy. However, these accuracy results only used binary classification and are time consuming for some practical clinical applications.

In [16], a three-label classification problem was studied whereby the distinction was made between continuous ictal epilepsy patients, intermittent epilepsy patients, and healthy subjects. The researchers used a SVM-based recognition system achieving an accuracy of 93.9%.

In terms of related work that is based on the data set that is being used in this research study, the following is provided. In [25], the researchers use deep learning methods to predict epileptic seizures. The authors used a deep learning classifier to distinguish the signals before and after a seizure. Then, the classifier performance was tested on held-out data from all patients and compared against the performance of a random predictor. The predicting system was modified to adjust each patient's feature set. Thus, the prediction system was made adaptable so that each patient could either choose 'sensitivity' or 'time in warning'. Therefore, this system can provide time and functional seizure prediction.

In [26], the authors built a deep learning model with automatic learning features. More specifically, a CNN (convolutional neural network) as deep learning method was used to learn the data. The resulting model provided information regarding the different types of interictal epileptiform discharges (IEDs) within the group, and was invariant to time differences between the IEDs. IEDs are pathological patterns of activity between seizures the brain of patients with epilepsy generates.

In [27], the authors trained deep neural networks with EEG data for predicting the seizure. Simultaneously, the authors collected spectral, temporal and spatial information for the analysis of seizures. Their study mostly focused on the cross-patient study of predicting the seizure. The results proved that the deep learning model generalizes well among different patients.

Research presented in [28] applied traditional machine learning algorithms, such as Linear SVM, Logistic Regression, KNN (K Nearest Neighbors). Furthermore, Neural Networks such as CNN, RNN (Recurrent Neural Networks), and LSTM (Long Short-Term Memory) were used for the prediction.

The research presented in this paper is an extension of the work presented in [29] where different neural network architectures/configurations were applied to the ensemble and the Choquet fuzzy fusion method.

3 Approaches

In this section, the methods applied are described. First, recurrent neural networks, ML algorithms, and deep neural networks are introduced followed by the Ensemble learning method and the Choquet integral fusion approach.

3.1 RNN

Recurrent Neural Network (RNN) is a special type of feedforward neural network that contains an internal memory. RNN has recurrent connections that perform the same function for every input of data. The output of each input depends on the past computation. After the output is computed, the result is sent back and serves as the input for the nodes again. In order for the RNN to make a decision, the current input and output that was learned from the previous input is considered. The difference of a RNN and a feedforward neural networks is that a RNN can use its internal state (memory) to process the sequences of inputs. This property makes RNNs able to accomplish tasks such as handwriting recognition or speech recognition [30], [31].

3.2 ML Algorithms

Machine learning provides systems the ability to automatically learn from experience without being explicitly programmed for a specific task. This learning is accomplished by either a supervised or unsupervised learning method depending on the goal of the learning task. Supervised methods are used when we have a variable whose value has to be predicted. In the unsupervised case, the data is not labeled and there is no value to predict or classify and thus the learning task is to identify common patterns among the input data. There are many learning algorithms available and researchers are always looking for the best algorithm that will perform well on a particular data set. The main objective of ML techniques is to train a model that can then be used to perform classification, prediction, estimation, or any other similar tasks [32].

3.3 Deep Neural Networks

Deep learning is a category in machine learning that involves artificial neural networks. Architectures that belong to deep learning are deep neural networks (DNN), deep belief networks, recurrent neural networks and convolutional neural networks. These have been widely applied to many different research areas such as speech recognition, natural language processing, audio recognition, computer vision, bioinformatics, gaming, and many more. A DNN [33] consists of an input layer, several hidden layers, and an output layer. The network is trained using backpropagation in order to minimize the error between the actual output and the desired output.

3.4 Ensemble

The concept of ensemble learning was first introduced in 1979 [34], which proposed using an ensemble system in a divide-and-conquer fashion, whereby the feature space was partitioned using two or more classifiers. More than 10 years later, another ensemble system was introduced showing that the generalization performance of similar neural network configurations can be improved using ensembles by introducing the variance reduction property [35]. However, research in [36] placed ensemble systems at the center of machine learning research. This was achieved by proving that a strong classifier in the probably approximately correct sense can be generated by combining weak classifiers through a procedure called boosting.

Ensemble methods are heavily used in the machine learning community due to their success primarily in classification tasks. Ensemble methods can be described as a technique that trains multiple learning algorithms, which achieve significantly higher accuracy than a single learner [37]. The common methods that are used are boosting, bagging, stacking, and a combination of base learners.

Boosting uses a model that was trained on data and then incrementally constructs new models that focus on the errors in the classification made by the previous model. An example of boosting is XGBoost [38].

Bagging involves the training of models on random subsamples. Then, each model votes with equal weight on the classification. For example, Random forest uses a bagging approach to allow the selection of a random set of features at each internal node to be used [39].

Stacking takes that output of a set of models and feeds them into another algorithm that combines them in order to make a final prediction. For this, any set of base learners and combiner algorithm can be used. The combiner algorithm takes the predictions of the models and combines them with a simple or weighted average approach.

3.5 Choquet

The data fusion process of the Choquet method is as follows. The data set is provided to the three different models (RNN, ML, and DNN), then the fusion is performed by taking the learned densities as well as the classification performance of the three models, and the result is the classification performance based on a test set.

The Choquet Integral (ChI) [40] - [43] is a well-known parametric function for data and information fusion. In particular, ChI is a generator function that is parametrized by the so-called Fuzzy Measure (FM), which is monotone and normal. Once the FM has been determined the ChI turns into a specific aggregation operator [44].

The basic idea of a fusion algorithm is that the algorithm should prioritize the most accurate evidence among the different inputs while never disregarding any contribution an input makes. The Choquet fuzzy integral conducts this via a non-linear weighted average calculation of all data sources. From a so-called defined fuzzy measure, the incoming evidence is weighted by a fuzzy measure value and this is summed over to produce a single confidence value. Usually, the Sugeno λ-measure is used. The Sugeno λ-measure needs to be initialized for the data source subsets. These data source subsets can be thought of as different values of importance of each data source. These values of importance are called densities and are often defined either by experts or by some metric. In our experiments, the AUC (Area Under the Curve) of ROC curves is used. Thus, the nonzero λ-value can be solved as to obtain the fuzzy measure components, and then the final Choquet fuzzy integral values can be computed for every classifier [45]. For more detailed information as well as the equations please refer to [46].

4 Experiments and Results

In this section, the data set used is described followed by the models used, and the experiments conducted as well as their results.

4.1 Data Set Description

The Epileptic Seizure Recognition data set [47] contains 4,097 data points collected from a EEG recording whereby each data point represents the value of the EEG recording at a particular point in time. 500 individuals were recorded to obtain the data points. The data was divided and shuffled into 23 chunks. Each chunk contains 178 data points (features). Thus, the 23 chunks times 500 individuals results in an overall value of 11,500 rows and 178 columns plus the last column representing the class label. The class label contains 5 labels:

- 1: Recording of seizure activity

- 2: Recording of tumor area
- 3: Recording from the healthy brain area
- 4: Recording when patient had their eyes closed
- 5: Recording when patient had their eyes open

In the past, this data set was primarily used as a binary data set where classes 2, 3, 4 and 5 were categorized as not having an epileptic seizure, versus class 1 having an epileptic seizure. However, binary classification is easier, thus this data set was used for a multi-label classification study.

The class distribution is as follows totaling 8,627 samples/rows:

- Class 1: 1,735
- Class 2: 1,732
- Class 3: 1,693
- Class 4: 1,744
- Class 5: 1,726

4.2 Results of State-of-the-Art Machine Learning Approaches

Table 1 shows the results of applying standard machine learning techniques. The accuracy results are provided for the following approaches Support Vector Machines (SVM), Decision Tree (DT), Logistic regression (LR), Gaussian Nearest Neighbour (GNN), Random Forest Classifier (RFC), Extra Tree Classifier (ETC), and Gradient Boosting Classifier (GBDT). The best AUC result was achieved by the GNN algorithm with 59.59% followed by SVM and DTC with 57.08% and 56.01%, respectively. As for the accuracy, ETC scored best with 69.08% followed by RC and GBC with 67.86% and 62.47%, respectively.

4.3 ML Ensemble and Choquet

The experiments were conduced in the following way. The three ML models were trained first. Then, using the results from these models the ensemble model is obtained by average ranking. The Choquet integral fusion is done using the three ML models together with the learned densities to build the classification model.

4.3.1 Models

The following ML algorithms were used with their corresponding parameters:

- RandomForestClassifier
  $n\_estimators$=100
  n_jobs=-1
  $criterion$='gini'
- ExtraTreesClassifier
  $n\_estimators$=100
  n_jobs=-1
  $criterion$='gini'
- GradientBoostingClassifier
  $learning\_rate$=0.05
  $subsample$=0.5
  max_depth=6
  $n\_estimators$=50

4.3.2 Results

Fig. 1 shows the confusion matrices obtained from the three ML models. Model ML2 is the best followed by ML1, and ML3 scores worst. Table 2 shows the results in form of AUC and accuracy. Only comparing the three ML models we can see that ML3 has the highest AUC score with 45.70%. In terms of accuracy though ML2 outperforms the other two models. Surprisingly, the Ensemble method does not achieve better results

Table 1: Machine Learning Results in %

	SVM	**DTC**	**LR**	**GNB**	**KNC**	**RFC**	**ETC**	**GBC**
AUC	57.08	56.01	51.56	**59.59**	44.45	39.84	38.87	44.04
Accuracy	54.85	33.88	22.47	43.06	47.41	67.86	**69.08**	62.47

only scoring best with ML3 in terms of AUC. The Choquet method however outperforms all by far with values of 47.42% and 79.10% for AUC and accuracy, respectively. Table 3 shows the MSE and RMSE results confirming the superior results of the Choquet method. The confusion matrices of the Ensemble method and the Choquet method are shown in Fig. 2.

4.4 RNN Ensemble and Choquet

The three RNN models were trained first and then the results were the input to the ensemble model that used average ranking. In addition, the Choquet integral fusion uses the three RNN model output together with the learned densities to build the classification model.

4.4.1 Models

The following RNN algorithms were used:

- SimpleRNN
- LSTM
- GRU

The parameter were the same for all three algorithms consisting of:

- ReLU activation function in dense layer
- Softmax activation function in output layer
- Adam optimizer
- Categorical cross-entropy loss function

4.4.2 Results

Fig. 3 shows the confusion matrices obtained from the three RNN models. Model RNN3 scores the best followed by RNN1. Table 4 shows the results in form of AUC and accuracy. Only comparing the three RNN models we can see that RNN1 has the highest AUC score with 48.68%. In terms of accuracy though RNN3 outperforms the other two models. Again surprisingly, the Ensemble method does not achieve better results, however, the Choquet method outperforms all by far with values of 51.46% and 68.94% for AUC and accuracy, respectively. Table 5 shows the MSE and RMSE results confirming the Choquet method to be the winner. The confusion matrices of the Ensemble method and the Choquet method are shown in Fig. 4.

4.5 DNN Ensemble and Choquet

Again, the three DNN models were trained first. Then, the outputs from these models were fed into the ensemble model applying average ranking. The Choquet integral fusion also uses the three DNN models as input together with the learned densities to build the classification model.

4.5.1 Models

Figure 5 shows the three DNN models that were used for the investigation. The three models contain three, two and four hidden layers with a

Table 2: AUC and Accuracy Results of ML in %

	ML1	**ML2**	**ML3**	**Ensemble**	**Choquet**
AUC	39.14	37.76	45.70	45.70	**47.42**
Accuracy	68.21	69.74	63.13	67.20	**79.10**

Table 3: MSE and RMSE Results of ML

	ML1	**ML2**	**ML3**	**Ensemble**	**Choquet**
MSE	0.830261	0.831304	1.160000	0.737391	**0.685565**
RMSE	0.911187	0.911759	1.077033	0.858715	**0.827989**

Table 4: AUC and Accuracy Results of RNN in %

	RNN1	**RNN2**	**RNN3**	**Ensemble**	**Choquet**
AUC	48.68	44.80	44.22	44.22	**51.46**
Accuracy	49.50	49.04	51.10	42.37	**68.94**

Table 5: MSE and RMSE Results of RNN

	RNN1	**RNN2**	**RNN3**	**Ensemble**	**Choquet**
MSE	2.283478	1.988870	2.169739	1.968000	**1.439304**
RMSE	1.511118	1.410273	1.473003	1.402854	**1.199710**

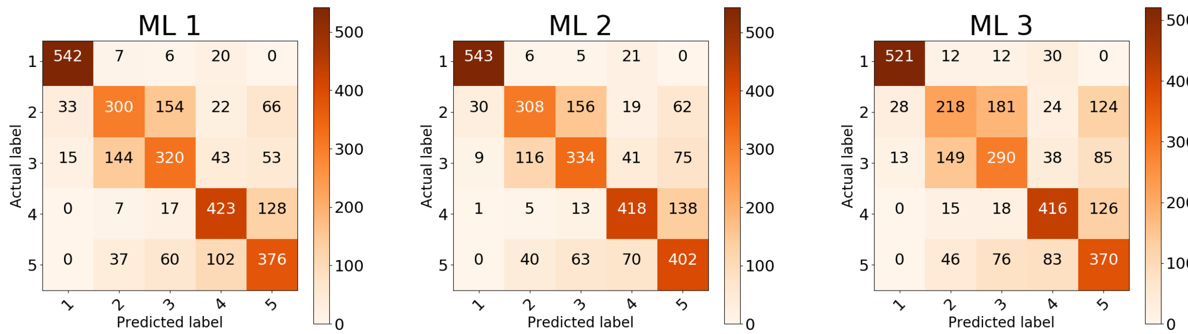

Figure 1: Confusion Matrices of ML Models

softmax function at the output.

4.5.2 Results

Fig. 6 shows the confusion matrices obtained from the three DNN models. Model DNN3 is the best followed by DNN1, and DNN2 scores worst. Table 6 shows the results in form of AUC and accuracy. Only comparing the three DNN models we can see that DNN2 has the highest AUC score with 42.07%. In terms of accuracy though DNN3 outperforms the other two models. Surprisingly, the Ensemble method does not achieve better results, however, the Choquet method outperforms all by far with values of 50.72% and 89.57% for AUC and accuracy, respectively. Table 7 shows the MSE and RMSE results confirming the superior results of the Choquet method. The confusion matrices of the Ensemble method and the Choquet method are shown in Fig. 7.

4.6 Comparison

Table 8 shows the comparison of the three approaches (RNN, ML, DNN) using the Choquet fusion technique. The results are given in terms of AUC and accuracy. What can be seen is that the Choquet fusion based RNN method scores best in terms of AUC, however, the Choquet fusion based DNN method obtains the best accuracy.

5 Conclusion

The Choquet fuzzy integral fusion method had shown very good performance applied to fused CNN model results that were trained on image data. This paper investigated the epileptic seizure recognition data set using three different methods namely RNN, ML and DNN and then compared their ensemble fusion method with the Choquet fuzzy integral fusion method. The three different approaches (RNN, ML, DNN) were trained and then the ensemble method and the Choquet fusion method were applied. The evaluation measures used were confusion matrix, AUC, accuracy, MSE and RMSE.

The results showed that the Choquet fuzzy integral fusion method on the whole outperforms the ensemble method as well as other state-of-

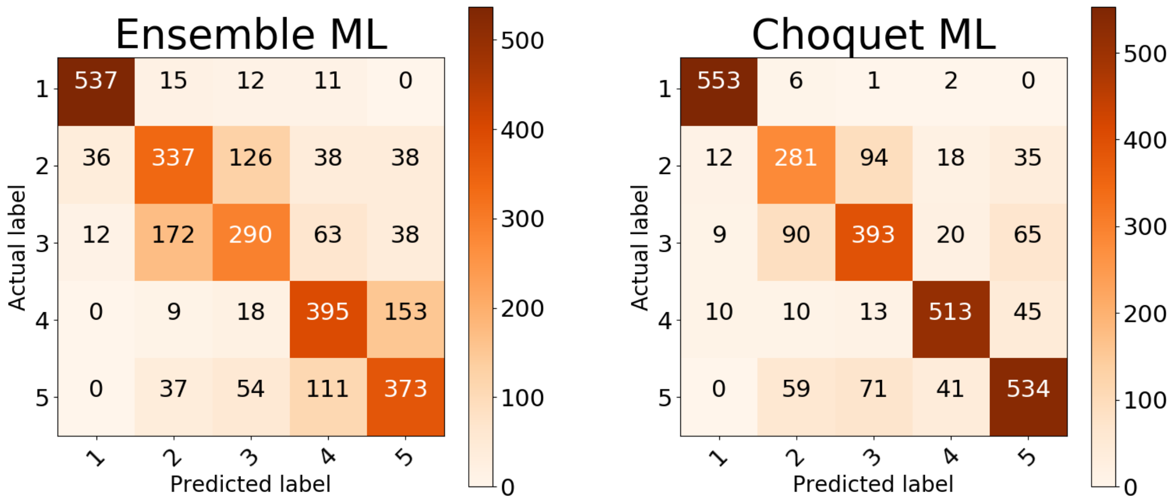

Figure 2: Confusion Matrices of Ensemble and Choquet Methods for ML

Table 6: AUC and Accuracy Results of DNN in %

	DNN1	DNN2	DNN3	Ensemble	Choquet
AUC	41.29	42.07	36.93	36.93	**50.72**
Accuracy	61.95	57.95	64.21	63.37	**89.57**

the-art classification methods. In particular, the AUC and accuracy results with values of 50.72% and 89.57%, respectively compared to 36.93% and 63.93% achieved by the ensemble method. Furthermore, a comparison with state-of-the-art classification algorithms showed that the Choquet fusion method is far superior to the best performing ML algorithm that achieved only 69.08% accuracy.

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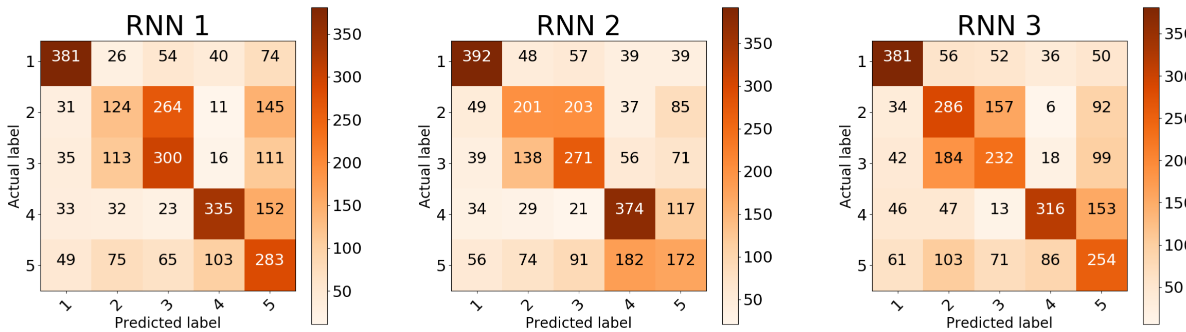

Figure 3: Confusion Matrices of RNN Models

Table 7: MSE and RMSE Results of DNN

	DNN1	**DNN2**	**DNN3**	**Ensemble**	**Choquet**
MSE	0.958957	1.273391	0.988870	0.716870	**0.392000**
RMSE	0.979263	1.128446	0.994419	0.846682	**0.626099**

Table 8: AUC and Accuracy Results of Choquet fusion based RNN, ML, and DNN Approaches

	RNN	**ML**	**DNN**
AUC	**51.46**	47.42	50.72
Accuracy	68.94	79.10	**89.57**

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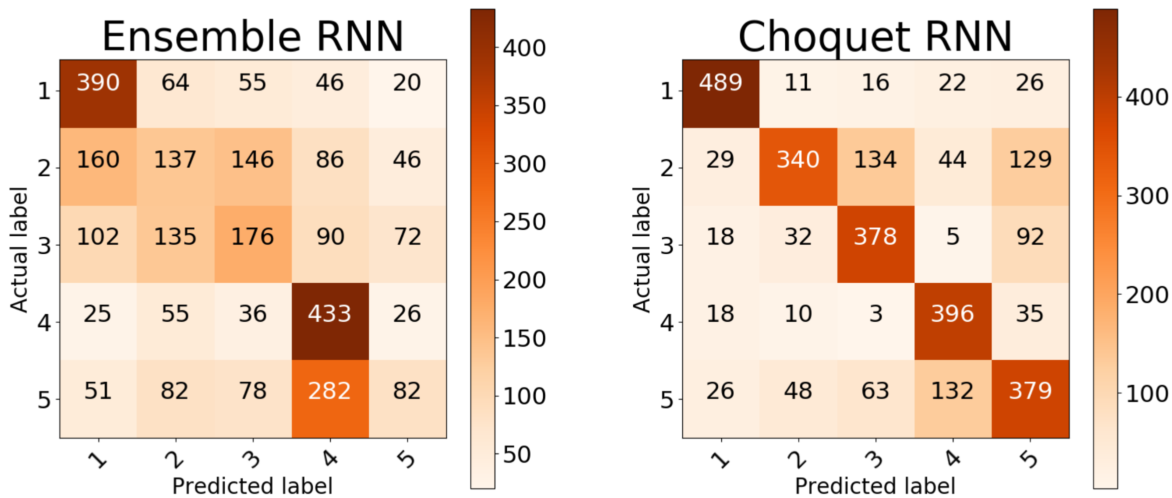

Figure 4: Confusion Matrices of Ensemble and Choquet Methods for RNN

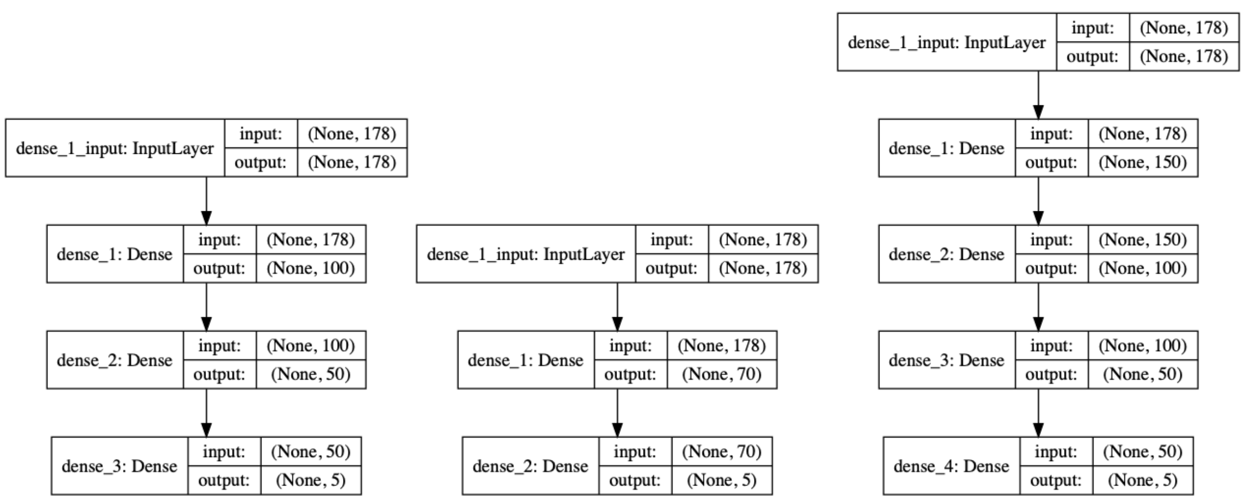

Figure 5: Three DNN Models

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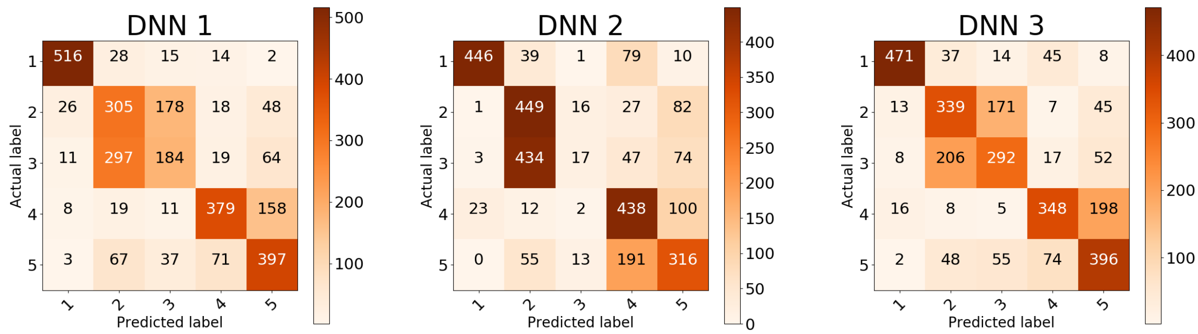

Figure 6: Confusion Matrices of DNN Models

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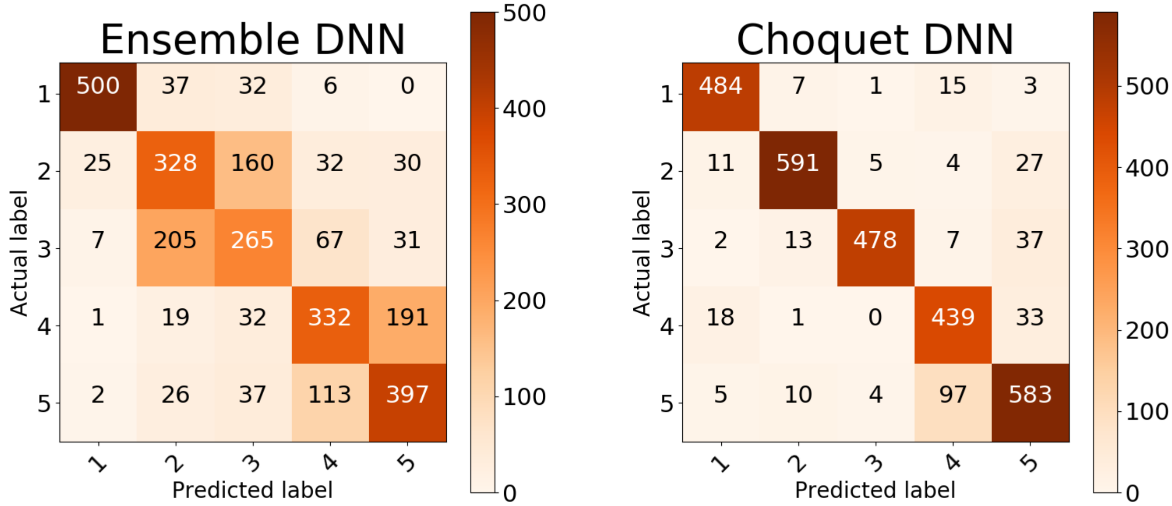

Figure 7: Confusion Matrices of Ensemble and Choquet Methods for DNN

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