Forecasting of Campus Placement for Students Using Ensemble Voting Classifier

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Authors' contributions

This work was carried out in collaboration between both authors. Author SD designed the proposed method, coding, statistical work and wrote the first draft. Authors SKB initiates the work and edited all processes before finalizing the manuscript. Both author read and approved the final manuscript.

Original Research Article

ABSTRACT

Campus placement is a measure of students' performance in a course. A forecasting method is proposed in this paper to predict possible campus placement of any institution. Data mining and knowledge discovery processes on academic career of students are applied. Supervised machine learning technique based classifiers are used for achieving this process. It uses an ensemble approach based voting classifier for choosing best classifier models to achieve better result over other classifiers. Experimental results have indicated 86.05% accuracy of ensemble based approach which is significantly better over other classifiers.

Keywords: Campus placement prediction; ensemble voting classifier; automated tool; higher education system; machine learning.

1. INTRODUCTION

Securing good percentage in examination as well as handsome-salary based campus placement is considered as evaluation metric for higher education systems [1]. A high-scale placement signifies a well-reputed organization and high-rated yearly admissions. Hence, a recommender

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system is proposed in this paper. It will automatically predict campus placement for the upcoming session. This prediction will assist an academic organization to take extra measures for improving placement. In fact, this prediction will also benefit students to work hard towards improvement their education.

Historical information of an organization will help predictive models to guide the students as well as organization. Past records of students will accelerate the process of obtaining new information related to prediction [2]. Data mining and knowledge discovery approaches are considered for obtaining an automated tool for forecasting campus placement. This paper employs a couple of supervised machine learning algorithms that consider past records of an organization as inputs and provide campus placement prediction. To address the problem of campus placement prediction, classification techniques are considered that maps input variable to target classes by considering training data. The input variables include several parameters such as, percentage obtained in preceding examinations, specialization, and work experience. All these data turn out to be good predictors whether a student can be placed or not. The predictive models can act as a tool to provide the information of students about their performance in the classroom and their chances of placement which in turn help the authorities to take informed decisions and maximize the results of the efforts made by the institutions. Using these data a predictive model can be obtained that provide information of students about their performance throughout their academic career and their opportunities of placement.

This paper employs machine learning algorithms that categorize the students on the basis of likelihood to get placed or not. The campus prediction problem considered in this paper is a binary classification problem. A couple of classifiers are addressed in this paper and their results are compared with respect to performance measure metrics. After comparing these supervised methods, the best two models are chosen. An ensemble approach based voting classifier is proposed in this paper that combines the best two classifier models. Combining best classifiers into a single platform is the strategy of voting ensemble method. Finally, experimental results indicate that voting classifier achieve better efficiency in terms of placement prediction [1].

2. RELATED WORK

In [1] two supervised machine learning classification algorithms such as Naïve Bayes classifier and K-nearest neighbor classifier are used that exploit previous year's historical data and predict placement probabilities. These classifiers take the parameters such as CGPA, USN, Tenth and PUC/Diploma results, Technical and Aptitude Skills as inputs. Incorporating more parameters into the classifier models may enhance the prediction outcomes which is future indication of this paper.

Some researchers use Decision tree and Random forest classifiers to predict placement possibilities of undergraduate students. Experimental results in [1] indicate that Random forest classifier provides significant prediction results over Decision Tree classifier in terms of Accuracy, Precision and Recall.

Several qualitative aspects of a student's profile such as CGPA, academic performance, backlogs, internship, future studies, technical skills, and communication skills are used while designing a predicting model in [3] which can forecast the recruitment possibilities of a student. For this purpose ID3 (Iterative Dichotomiser 3) classification technique [3] based on decision tree has been applied.

In [4] campus placement predictions are obtained using the machine learning algorithms such as J48, Naïve Bayes, Random Forest, Random Tree, Multiple Linear Regression, binomial logistic regression, Recursive Partitioning and Regression Tree (RPART), conditional inference tree (CTREE) and Neural Network (NNET) algorithms. All these classifiers accept parameters such as performance in placement assessment examinations conducted by assessment agencies, communication skills, previous year's record etc. while predicting campus placement probabilities.

In [5], several Decision tree algorithms such as ID3, CHAID, and C4.5 were implemented and applied on datasets for campus placement prediction. Experimental results indicated that ID3 technique performs best with respect to other algorithms.

A placement predictor system (PPS) is proposed in [6] that uses logistic regression model. In order to optimize the classifier to obtain optimum

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values of parameters with minimum value of cost function, Gradient descent algorithm is applied.

A couple of classifiers such as J48, Bayesian, K-nearest neighbour, one R and J Rip were used in [7] to predict students' performance using attributes such as personal profile, secondary educational score, entrance exam score, admission year, etc. All the mentioned classifiers are trained using 10-fold cross validations. It is concluded that J48 classifier achieves highest overall accuracy.

Students' real data of Maejo University in Thailand is used in [8] to determine graduate employability. For this purpose, various algorithms of Bayesian Network and Decision Tree have been employed to build the classification model for detecting graduate employability.

3. PROPOSED METHODOLOGY

Campus placement is important activity from an academic organization as well as student's point of view. Companies often visit the college for identifying bright students and offer job opportunities to them. They check several factors like examination marks, work experience, specialization while selecting students from colleges. This paper contributes to placement prediction system by obtaining an automated tool considering above stated affecting factors. The
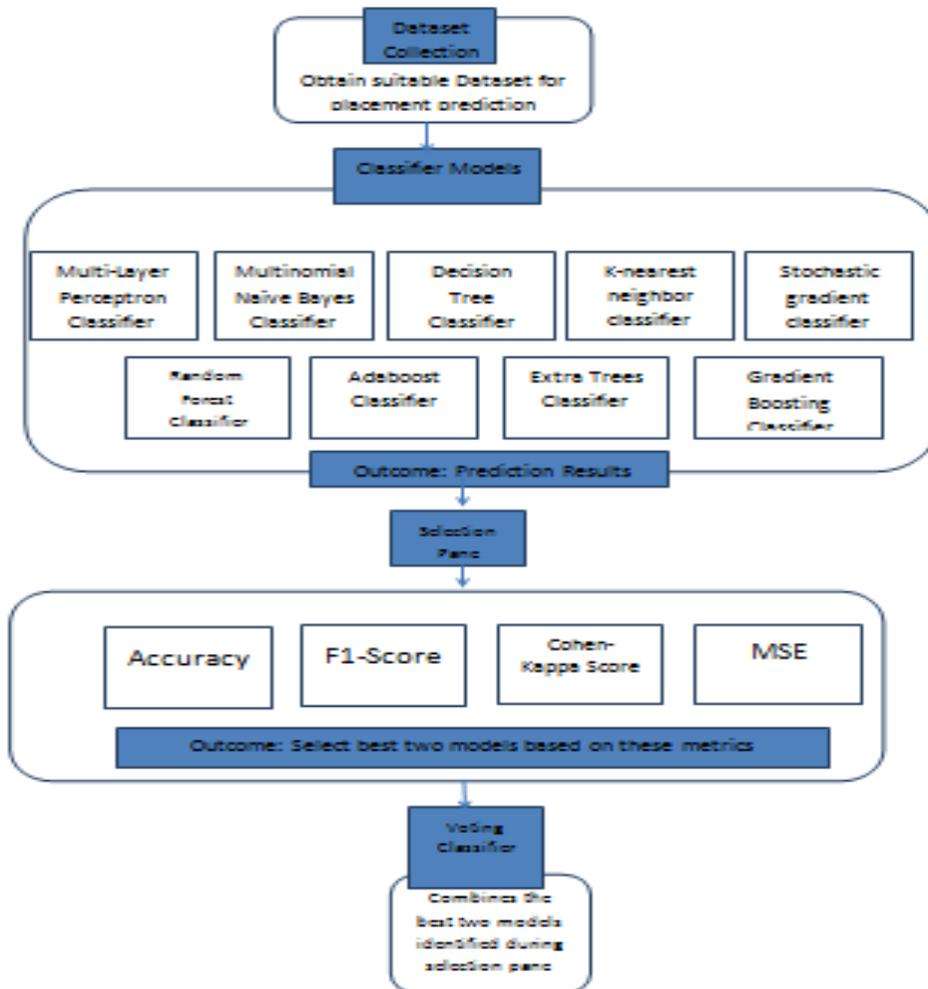

Fig. 1. System flow diagram of the proposed methodology

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automated tool proposed in this paper focuses on predicting the likelihood of students' placement. The methodology proposed in this paper focuses on obtaining Voting strategy based ensemble classifier that forecasts the student placement. This methodology implemented in this paper follows a multi-step procedure. The system flow diagram of this methodology is shown in Fig. 1. In subsequent sections different modules related to the proposed method are explained.

4. DATASET COLLECTION

In this framework, a dataset from kaggle [9] is used for predicting campus placement for any institution. The dataset can be formulated as collection of attributes. The attributes include several criterions for achieving placement prediction. Marks obtained in previous examinations, specialization, work experience, status (placed/not placed) etc. are included in the attribute list. However, the attribute 'status' is utilized as a target class of the prediction.

For better understanding of the target as a baseline, a multistep procedure is followed by obtaining a balanced dataset. The multistep procedure begins with preprocessing of these data. Preprocessing techniques include missing values handling, irrelevant attribute elimination etc. An encoding process is applied on this pre-processed data to transform non-numeric data into numeric data. This transformation of data is required to provide suitable data to be fitted to any classifier. Before fitting the data into any classifier, preprocessing of the data is required. Preprocessing techniques include missing values handling, irrelevant attribute elimination etc. An encoding process is applied on this pre-processed data to transform non-numeric data into numeric data.

5. CLASSIFIERS MODELS

A classifier maps input variable to target classes by considering training data. The objective of using classifier is to predict whether a student can be placed or not. A set of classifiers are employed in this framework that considers preprocessed and transformed data for predicting campus placement for students. The transformed data is partitioned into training set and test set with the ratio of 8:2. The training set is fitted to classifier model and later prediction is obtained for test set. The following diagram

Fig. 2. shows a general structure of a classifier model.

A couple of classifiers such as Multilayer Perceptron Classifier, Multinomial Naïve Bayes Classifier, Decision Tree Classifier, K-nearest neighbor classifier, Stochastic gradient classifier and Ensemble based classifiers such as Random Forest Classifier, Adaboost Classifier, Extra Trees Classifier, Gradient Boost Classifier are employed for training and classifier purpose.

A brief description of all classifiers used in this paper is provided as follows-

### 1. Multi-Layer Perceptron Classifier-

Multi-layer perceptron [10] can be used as supervised classification tool by incorporating optimized training parameters. For a given problem, the number of hidden layers in a multilayer perceptron and the number of nodes in each layer can differ. The decision of choosing the parameters depends on the training data and the network architecture.

2. Naïve Bayes Classifier-

The Naive Bayes classifier [11] is a supervised classification tool that exemplifies the concept of Bayes Theorem [12] of Conditional Probability. The decision made by this classifier is quite effective in practice even if its probability estimates are inaccurate. This classifier attains very promising result in the following scenario-when the features are independent or features are completely functionally dependent. The accuracy of this classifier is not related to feature dependencies rather than it is the amount of information loss of the class due to the independence assumption is needed to predict the accuracy [11].

3. Decision Tree Classifier-

A Decision Tree (DT) [13] is a classifier that exemplifies the use of tree-like structure. It gains knowledge on classification. The decision node or non-leaf node indicates certain test. The outcomes of these tests are signified either of the branches of that decision node. Each target class is denoted as a leaf node of DT. Starting from the beginning of the corresponding nodes of the tree is traversed through the tree until a leaf node is reached. In this way classification result from a decision tree is obtained [13].
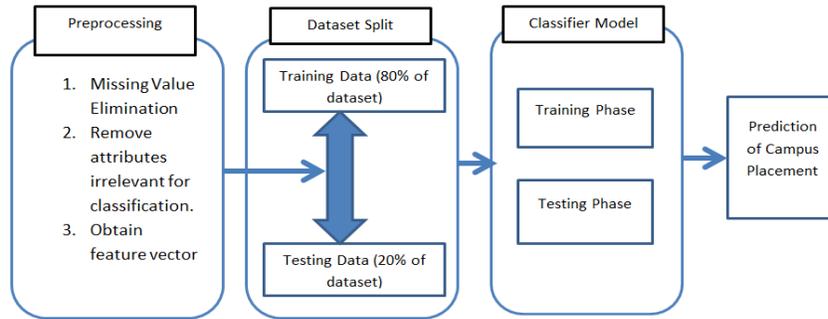
Fig. 2. General structure of classifier model

4. K-nearest neighbor classifier-

K-Nearest Neighbour Classifiers [14] are often known as lazy learners. The classifier proceeds by identifying objects based on closest proximity of training examples in the feature space. While determining the class, this classifier considers k number of objects as the nearest object. The main challenge of this classification technique relies on picking the appropriate value of k [14].

5. Stochastic gradient Descent classifier-

Stochastic Gradient Descent (SGD) [15] is capable of solving large scale supervised machine learning problems. It minimizes a number of loss functions and is applicable to Support Vector Machine (SVM) and Logistic optimizations. Stochastic gradient descent is common algorithm used in various Machine Learning algorithms. Gradient Descent is used as optimization technique in Machine Learning and Deep Learning. It can be used with most of the learning algorithms. Gradient means slope or slant of a surface. So gradient descent literally means descending a slope to reach the lowest point on that surface. Gradient descent used iteration that starts from a random point on a function and travels down its slope in steps until it reaches the lowest point of that function SGD algorithm is used to enhance performance in text classification [15].

6. Ensemble based classifier-

Ensemble approach facilitates several machine learning algorithms to perform together to reach higher accuracy of the entire system.

  a. Random Forest Classifier-

Random forest (RF) [16] exploits the concept of ensemble learning approach and applies regression technique for classification based problems. This classifier is a combination several tree-like classifiers which are applied on various sub-samples of the dataset and each tree cast its vote to the most appropriate class for the input.

  b. Adaboost Classifier-

Boosting is an efficient technique that is applied on combination of several unstable learners in order to improve accuracy of classification [17]. Boosting technique applies classification algorithm to the reweighted versions of the training data and chooses the weighted majority vote of the sequence of classifiers. AdaBoost [18] is a good example of boosting technique that produces improved output even when the performance of the weak learners is inadequate.

  c. Extra Trees Classifier-

Extra Trees Classifier [19] belongs to the category of ensemble learning technique. It aggregates the outcomes of various de-correlated decision trees collected in a "forest" and delivers output as classification result. This classifier is quite similar to Random Forest Classifier but the construction of this classifier contrasts from Random Forest Classifier making policy.

  d. Gradient Boost Classifier-

Gradient boosting algorithm [20] is another boosting technique based classifier that exploits the concept of decision tree. It also minimizes the prediction loss. It checks models which decrease the loss function

obtained from trained samples. From these calculations the errors are measured and analysed for optimal prediction of results. Loss function calculates the range of detected rate which compares with desired target. Onward stepwise process is most popular method for updating different with various attributes. The accuracy is optimized by reducing loss function and adding base learners at all stages.

6. IMPLEMENTATION OF THE CLASSIFIERS

In this framework classifiers are trained using appropriate parameters. For maximizing the performance of these models, default parameters may not be sufficient enough. Adjusting these parameters will produce enhanced predictive models which may be regarded as the optimised one while detecting recruitment possibilities.

This framework utilised MLP classifier as a collection of 5 hidden layers of size 128, 64, 32, 16 and 8 respectively. The K-NN classifier gives a promising result for the value k=5 considering all the evaluating metric. For naïve bayes classifier, multinomial naïve bayes classifier is employed which follows a multinomial distribution of each features. The decision tree classifier implemented in this paper uses Gini index [21] while choosing objects from dataset. The nodes of the decision tree are expanded until all leaves are pure or until all leaves contain less than minimum number of samples. In this case, minimum number of samples is assigned a value as 2.

On the other hand, ensemble classifiers, such as, Random Forest, AdaBoost and Gradient Boost classifiers are built based on 500 numbers of estimators on which the boosting is terminated. After constructing these classification models, training data are fitted into it. Later the testing dataset are used for prediction purpose. After the prediction is done, performance of the classifiers are evaluated based on the predicted value and the actual value.

7. SELECTION PHASE AND PERFORMANCE EVALUATION METRICS

While evaluating performance skill of a model, it is necessary to employ some metrics to justify the evaluation. During selection phase, the aforementioned classifier models are compared with respect to the following performance evaluation metrics. Use of these metrics will assist in identifying best problem solving approach.

1. **Accuracy-**

   Accuracy [22] is a metric that ascertains the ratio of true predictions over the total number of instances considered. However, the accuracy may not be enough metric for evaluating model's performance since it does not consider wrong predicted cases with different weights.

2. **F1-Score-**

   For compensating the above mentioned problem, we consider two more metrics known as, Recall and Precision. *Precision* [22] identifies the ratio of correct positive results over the number of positive results predicted by the classifier. *Recall* [22] denotes the number of correct positive results divided by the number of all relevant samples. *F1-Score* or *F-measure* [22] is a parameter that is concerned for both recall and precision and it is calculated as the harmonic mean of precision and recall.

3. **Cohen-kappa Score-**

   Cohen-Kappa Score [23] is also taken into consideration as an evaluating metric in this paper. This metric is a statistical measure that finds out inter-rate agreement for qualitative items for classification problem.

4. **MSE-**

   Mean Squared Error (MSE) [22] is another evaluating metric that measures absolute differences between the prediction and actual observation of the test samples.

Mathematically, the aforementioned metrics can be defined as follows with given True Positive, True Negative, False Positive, False Negative as TP,TN,FP,FN respectively-

Accuracy= TP+TN/(TP+FP+TN+TP)

Recall= TP/(TP+FN)

Precision= TP/(TP+FP)
F1- Measure or F1-Score= 2* Recall * Precision / (Recall + Precision)

Cohen-Kappa Score= $(p_0-p_e)/(1-p_e)$

where p_o denotes relative observed agreement among raters and p_e is the probability of agreement by chance.

MSE= $(\sum_{i=1}^{N}(Xi - Xi')^2$ / N) where Xi is the actual value and Xi' is the predicted value.

Lower value of MSE and higher values of accuracy, F1-Score, and Cohen-kappa score signifies a better performing model.

After computing these evaluation metrics for each classifier, the top two classifier models are identified and used as input for voting classifier.

8. VOTING CLASSIFIER

A Voting classifier [24] provides a platform where multiple dissimilar models are combined into a single model. The objective of this classifier is to design a model that is stronger than the other individuals. All the above mentioned classifiers are implemented for campus placement prediction. Prediction results are compared and best two models are selected in selection pane. After that, the prediction results of best two models are combined for obtaining a prediction result that is superior over all the results. A voting classifier is proposed in this framework that is based on ensemble technique. This method combines selected models for obtaining better prediction for campus placement.

9. EXPERIMENTAL RESULTS

In this section, performance of each of the aforementioned classifiers is shown with respect to performance evaluation metrics (from Table 1 to Table 9).

The most widely used decision tree algorithm is C4.5. It is better than ID3 algorithm. In both the methods, accuracy, F1-Score, Cohen-Kappa Score and MSE are far less optimised than the proposed method. J48 algorithm is another method like C4.5 decision tree algorithm in Weka software tool. In this method condition of some attribute of each internal node is examined and the outcome of the study is estimated from each branch of the tree represents. The process is continued up to leaves of the tree. This requires high processing time and in turn reduces accuracy to 70 %. The proposed method has higher accuracy without compromising to other performance parameters [5,6]. Weka is open source software that implements a large collection of machine leaning algorithms and is widely used in data mining applications. Many researchers apply classification and regression algorithms for estimating the accuracy of their model. The accuracy obtained by this method depends on the accuracy of the software which is less than the proposed model [2]. Some researchers use 10-fold cross-validation for evaluation of their approach. This model does not predict whether a new student will place or not in an organization [10].

Multi-Layer Perceptron Classifier-

Table 1. Overall performance of MLP classifier

PerformanceMeasure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
MLP Classifier	67.44%	0.67	0.25	0.33

Decision Tree Classifier-

Table 2. Overall performance of decision classifier

PerformanceMeasure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Decision Tree Classifier	69.77%	0.7	0.34	0.3

K-nearest neighbor classifier-

Table 3. Overall performance of K-nearest neighbour classifier

PerformanceMeasure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
K-nearest neighbor classifier	74.42%	0.74	0.42	0.26

Naïve-Bayes Classifier-

Table 4. Overall performance of multinomial naïve-bayes classifier

Performance Measure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Multinomial Naïve-Bayes classifier	76.74%	0.77	0.49	0.23

Stochastic Gradient Classifier-

Table 5. Overall performance of stochastic gradient classifier

Performance Measure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Stochastic Gradient Classifier	76.74%	0.77	0.48	0.23

Ensemble-based Classifier-

- **Random Forest Classifier**-

Table 6. overall performance of random forest classifier

Performance Measure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Random Forest Classifier	72.09%	0.72	0.37	0.28

Adaboost Classifier-

Table 7. Overall performance of adaboost classifier

Performance Measure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Adaboost Classifier	76.74%	0.7	0.34	0.3

Extra Trees Classifier-

Table 8. Overall performance of extra trees classifier

PerformanceMeasure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Extra Trees Classifier	79.07%	0.79	0.56	0.21

Gradient Boosting Classifier-

Table 9. Overall performance of gradient boosting classifier

PerformanceMeasure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Gradient Boosting Classifier	81.4%	0.81	0.59	0.19

10. ANALYSIS

From the aforementioned comparative analysis, it is quite observable that the ensemble method based Gradient Boosting Classifier provides best result with respect to all the evaluation metrics.

Next, Extra Trees Classifier also provides relatively better result than other classifiers except Gradient Boosting Classifier. During selection pane phase, these two classifiers are chosen for prediction. Next, a predictive model is proposed in this paper that combines the results

of these two classifiers for achieving better prediction as outcome. This proposed method implements ensemble approach based voting classifier. The purpose this method is to boost the prediction outcome by combining the best two classifiers obtained during selection pane. Following Table 10 shows the performance the proposed method in terms of evaluation metrics.

As shown in Table 10, proposed method performs significantly well over the other classifiers. Following Figs. 3 to 6 show comparative analysis of all the classifiers along with the proposed method.

From Fig. 3 to Fig. 6 indicate that with respect to all evaluation metrics, the proposed voting classifier outperforms well and can be used as a placement predictor. Voting is one of the simplest ways of combining the predictions from multiple machine learning algorithms. Voting classifier isn't an actual classifier but a wrapper for set of different ones that are trained and valuated in parallel in order to exploit the different
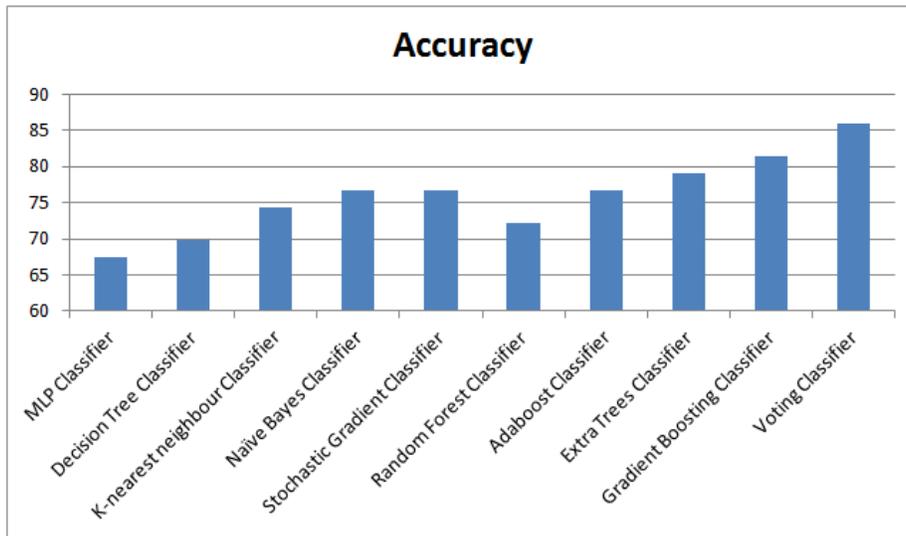

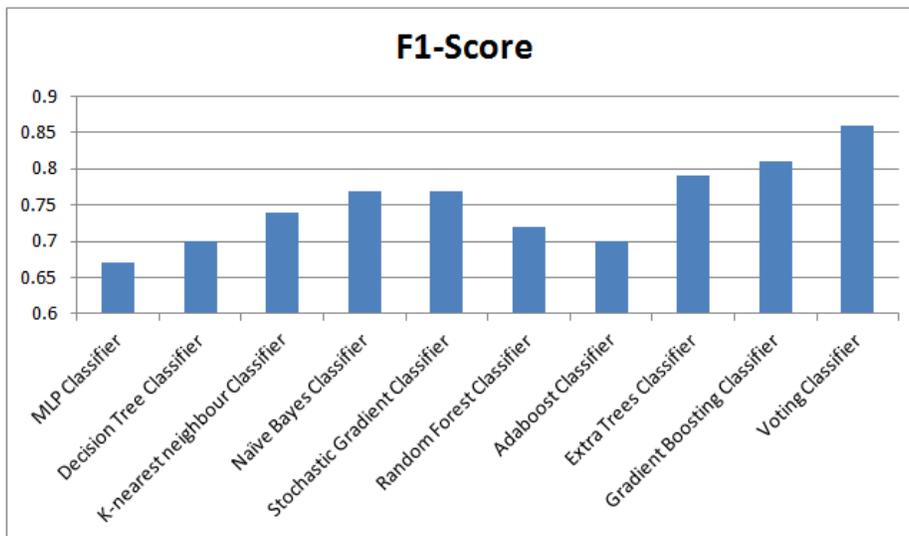**Fig. 3. Overall performance comparison of all classifiers with respect to accuracy**

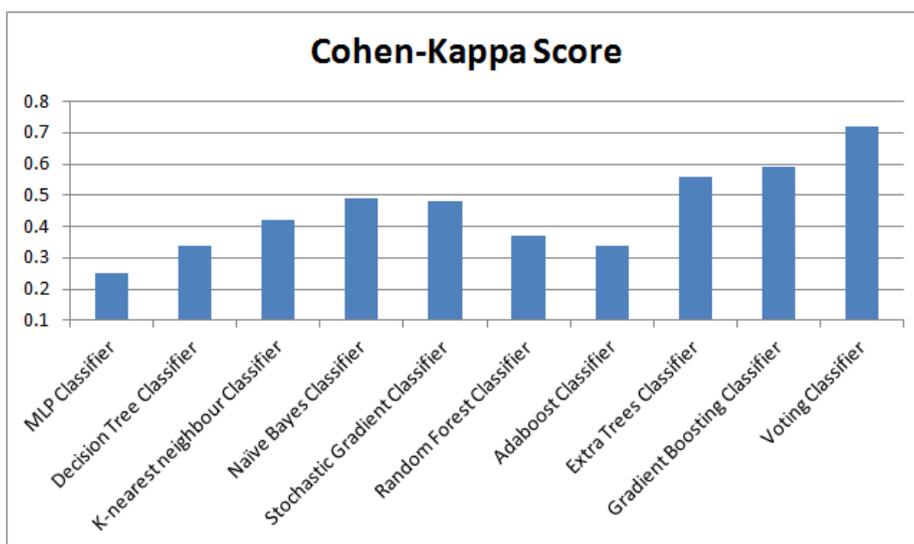**Fig. 4. Overall performance comparison of all classifiers with respect to F1-Score**

Fig. 5. Overall performance comparison of all classifiers with respect to Cohen-Kappa Score

Table 10. Overall performance of proposed voting classifier

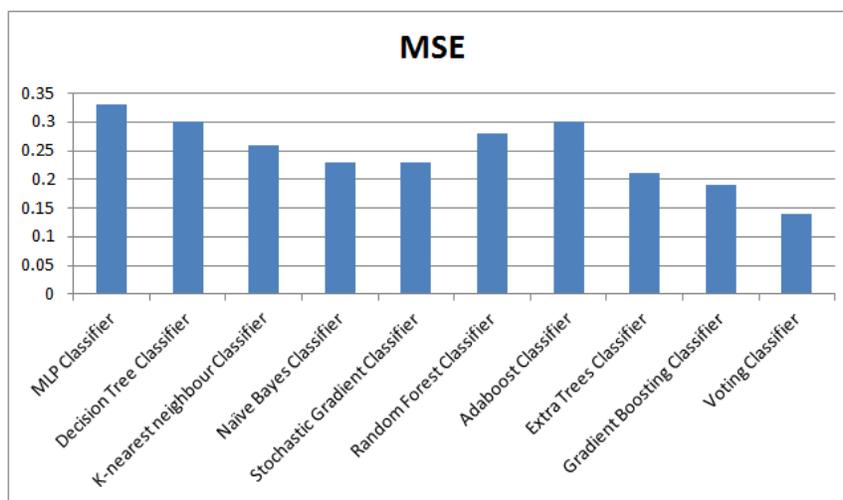| Performance Measure Metrics	Accuracy	F1-Score	Cohen-Kappa Score	MSE
Voting Classifier [Proposed Method]	86.05%	0.86	0.72	0.14

Fig. 6. Overall performance comparison of all classifiers with respect to MSE

peculiarities of each algorithm. In the proposed method the main aim is to show voting classifier is most suitable for classifying placement of student. From this study it is quite visible that assembling different classifiers into a wrapper class has worked significantly well in this field.

11. CONCLUSION

Campus placement plays significant role while analysing organization's as well as student's effort in higher education system. In this context to encourage student's better performance, a prediction has been carried out using

classification algorithms. Several classifiers are utilised while predicting campus placement. Top two classifiers are selected and utilised for ensemble method. Ensemble method is dependent on multiple algorithms those are trained on the same data set, or independent from the data, i.e., using statistical measures. The prediction of each participating classifier in the ensemble may be considered as a vote for a particular class, i.e., benign class or malware class. The ensemble's outcome is generally derived on the basis of different voting strategies. Different voting strategies may give different results depending upon different factors such as families of algorithms used. The ensemble based classifier performs better than individual classifiers in most of the cases. The basic idea is to show that voting classifier is capable for classifying placement of student. Placement Prediction problem addressed in this paper uses Voting ensemble based classifier that combines Gradient Boosting Classifier and Extra trees classifier. This combined prediction reaches an accuracy of 86.05%, F1-Score 0.86, Cohen-Kappa Score 0.72 and MSE 0.14 which is significantly better than other classifier models. The method helps to use effective measures for the proper placement of students. However, incorporating other parameters such as backlogs in examinations, behavior in class etc. into the investigation of campus placement may reach better efficiency of the prediction system.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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