Design Engineering A Comparative analysis of various Machines learning algorithm based predictive models for employability prediction of Indian Engineering Students

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A Comparative analysis of various Machines learning algorithm based predictive models for employability prediction of Indian Engineering Students

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Abstract

Early employability or job readiness prediction is an important technique in benefit of the student as well as educational organization. Based on the accurate prediction the constructive action can be taken. This paper presents a comparative analysis of different machine learning models for predicting the employability of the students learned upon the employability and personality test data set. The comparative analysis of the models shows that the ensemble models outperform the single models. Applying 10-fold cross validation on all 10 models the AdaBoost-Ensemble model showed better accuracy. The study proposes the optimization-based weighted ensemble learning prediction model to predict the employability outcomes for Indian engineering graduates.

Keywords: Machine Learning, Ensemble learning, Prediction Model, Student placement prediction, Higher Education system.

1. Introduction

Educational data has been exploding in recent years. This is attracting researchers to this area of study. Most of the research focuses on predicting students' academic success and employability.

The prediction models, based on self-reported data by student such datasets cannot be validated. The employability skills required by the candidate are majorly technical, personal skills and cognitive skills. These abilities are assessed in an employability skill test [1], and the results of

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these tests are considered by the majority of recruiters. Thus, this test data can improve the accurate of the research outcomes.

An extensive review of research focusing on education domain, student performance, prediction and employability prediction using different tools and technique is done by [2], whereas [3] focused on research undertaken from 2007 to 2018 for academic performance prediction using supervised learning and [4] reviewed different datamining approaches used for predictions in education domain.

A few studies show how the ensemble method can be used in a variety of situations, eventually leading to knowledge discovery and better predictions, [6] used the approach of RNN and applied ensemble RNN-EL model for stock

prediction, whereas [7] is a review of various researchers' recent contributions to ensemble learning, with a focus on deep neural networks, and training ensemble in distributed systems.

The researchers in [8] used a decision tree to characterize the graduate profile from the tracer analysis to predict their employability., whereas [9] used ANN, SVM, Decision tree, and Logistic regression to analyze the students' placement test results and found that C5 decision tree was the best performing model.

[10] developed a model to assess the significant relationship between student academic achievement and placement and found that Naive Bayes outperformed decision trees. Similarly, when applied to demographic and academic performance data of students, Naive Bayes performed better than KNN and oneR in [11]. In [12], the found that Logistic regression worked better as compared to Nave Bayes, J48, SimpleCART.

To handle multi-disciplinary and multidimensional large and unbalanced data set the clustering approach is suggested in [13], similarly [14] shows that Hurricane clustering gives good prediction when applied to academic and technical attributes. On the job training (OJT) data set was used by [15] and applied J48 algorithm which classified 85.5% of data correctly; in its further research [16] showed SVM as a better model. [17], determined J48 outperformed SVM and ANN.

[18] used a soft computing approach of fuzzy rule base with 27 rules on students' education and personal characteristics and suggested the formation of a more precise and reliable rule-based; [19] also suggested the use of a hybrid fuzzy model to boost classification; and [20] used a fuzzy logic-based recommender on the OJT dataset and achieved high predictive accuracy.

When experimenting with various data sets and machine learning algorithms, the researchers [21] proposed using an ensemble learning approach. As studied by [22] Ensemble learning accommodates range of weak learners that are combined to make higher results [23] discuss the benefits of ensemble learning and show that ensemble technique provides 10% higher

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performance than single model when applied to tutoring system on ASSISTment platform. [24] developed a option mechanism to predict the result of basketball; the hybrid ensemble framework is employed that shows high accuracy compared to single model like Naïve mathematician, ANN, Apriori, supplying regression, etc.

The author in [25] used ensemble learning for classifying different types of anaemia and found that ensemble approach of bagging and boosting showed higher accuracy. [26] used an ensemble voting classifier to forecast campus placement by combining two classifiers in an ensemble and came up with a successful prediction. They also proposed that other more relevant and related parameters that are directly related to student placement must be included.

Recent study of, [27] combined five classifiers over two outcomes for each classifier to form ensemble and result shows the ensemble model performed better classification; [28] focus on how combining different model can reduce the error and give better and accurate result by increasing diversity in ensemble model.

Majority of the student join higher education with perspective of getting employed after the course. Thus, the early prediction would help the student to improve and get job ready. Also, employability of the student is considered one of the factors that defines the success of an Educational Institute [31].

The objective of this paper is to present the advance Machine learning approach that would give more accurate prediction when applied to non-linear, large, multidimensional, and multivariate data. The paper also presents the comparison of different machine learning algorithm over the data set considered for the study.

2. Materials & Methods

The AMEO 15 Dataset [1] is used for this study. The data pre-processing and visualization is applied to understand and clean the data. After performing the pre-processing & visualization and feature selection. The dataset is split into training and testing with 70% and 30% of data, respectively. The machine learning algorithms are applied to the cleaned dataset. For getting started three bins were formed to classify the outcome as highly employable, moderately employable, and less employable.

The single models are trained and tested, and the accuracy is checked. This would help us get a good comparison amongst different algorithms and study and better understand the nature of the data further. We started with some basic algorithms those were used by most of the researchers in their work.

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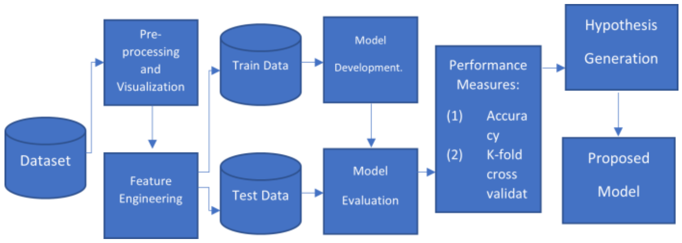

Figure 1. Workflow of the experimental set-up

2.1. Dataset

According to [30] employability skills required by the candidate are majorly technical, personal skills and cognitive skills. These skills are evaluated in the employability and personality test and the result of these skill test are considered by most of the recruiters. Thus, the data from employability test can help in achieving more accurate and precise results.

The data for this analysis came from the AMEO 2015 dataset, which was part of a data challenge [1]. The AMEO dataset (Aspiring Minds' Employability Outcomes) contains the results of Aspiring Minds' AMCAT exam. This exam evaluates employability metrics such as cognitive abilities, technological abilities, and personal characteristics. This database focuses on engineering graduates from India's 26 states. Tables 1 provide a summary of the dataset as well as information about the attributes.

Table 1. Dataset description

Characteristic of Dataset	**Multivariate**
Instances	3998
Attributes	38
Characteristics of attributes	Ordinal, Integer & Data-time
Missing Values	Yes

Different attributes are categorized into certain categories for better understanding. Each row represents different categories and the attributes those falls under specific category are listed in front of it. (See Table 2)

Table 2. Attribute description as per category

S.N.	**Category**	**Attributes**				
1	Personal	Gender	DOB			
2	Demograp	City	10th 12th	College		

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	hic		board city	State		
3	Academic	10th %	12th %	CGPA		
4	Personal Skill	Conscientiou sness	Agreeable ness	extraversion	Neuroticis m	Openness to experience
5	Cognitive Skill	English	Logical Ability	Quantitative aptitude		
6	Technical Skill	Domain specific				

2.2. Data Pre-Processing & Feature Engineering

Since most of the attributes have multivariate values and missing values, the dataset needed pre-processing. Certain characteristics, for example, self-reported attributes like City had to be redefined. Few manual edits were performed to correct these inconsistencies.

The data cleaning process removes any values that are inaccurate or contradictory. The columns that are not required are removed.

The method of one-hot-encoding is used for categorical functionality. The method of mean value imputation is used to solve the issue of missing values. Table 3 shows the modifications and cleaning for various attributes.

Table 3. Data Pre-processing for Attributes

Feature	**Pre-processing / Cleaning approach**
Gender	One-hot-encoding
DOB	Retained the year
Standardized test score	Replaced -1 to 0 (Not attempted)
Engineering specializations	Converted to core discipline
10th & 12th board	Corrected the self-reported and redundant values to one of “CBSE” , “ICSE” , “STATE” , “NA” Then one-hot-encoded it

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College ID, College City ID	Excluded
College GPA	It was ranging from scale of 10 to 100, for standardization it is converted in scales of 100
College state, specialization, graduation year, gender, degree, college tier	Encoding is done
Removing outliers	Salary > 1000000 is very rare, so such entries are removed

There were various specializations in the dataset, these were combined to the core specializations example. Computer Science, Computer Technology, Computer Engineering, Information Technology, etc are combined into CS. Figure 2 & 3 shows the same.

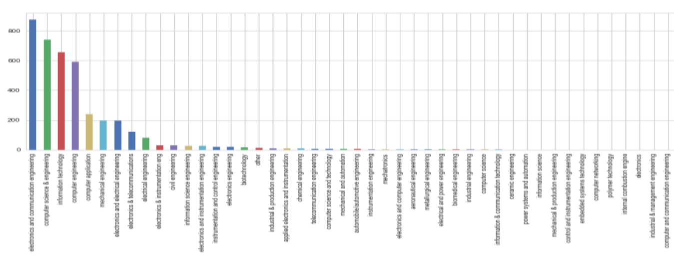

Figure 2. Specialization before cleaning

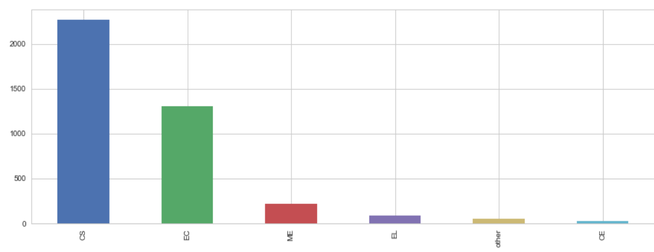

Figure 3. Specialization after cleaning

The GPA of the students were present on different scale ranging from 10 to 100, to standardize this attribute all the GPA are scale to 100.

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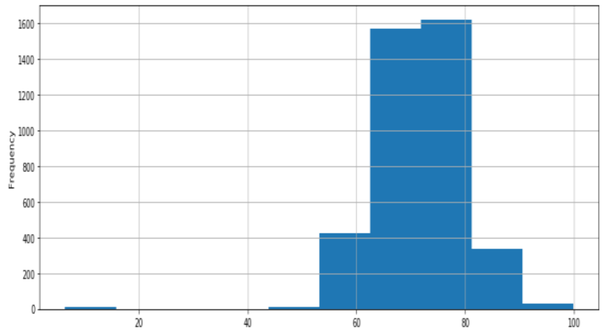

Figure 4. GPA before scaling

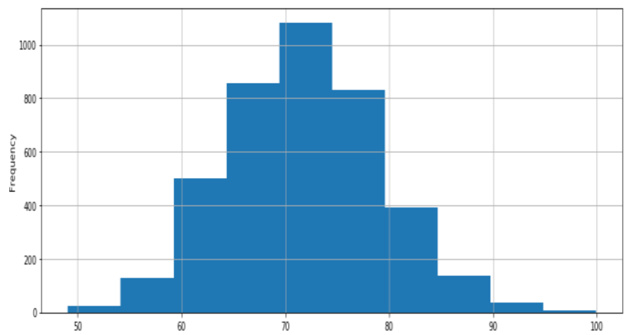

Figure 5. GPA after scaling

Data visualization aids in comprehending the essence of the data and thus reveals the dataset's insights. The visualization approach aids in the selection of suitable algorithms by providing a clearer understanding of the data.

The patterns and trends in the dataset are visualized. Questions that reveal the essence of the data are used to develop hypotheses.

2.3. Model Development: Learning Algorithms

Machine learning is growing widely and is dealing with numerous use cases across all the domains including education domain [29].

2.3.1. Decision Tree

Decision tree is used to classify the job-readiness through the salary slab of the candidates in the dataset.

With an entropy criterion and a maximum depth of 5, a decision tree is prepared. Where entropy is calculated as:

$$H(X) = -\sum_{i=1}^{n} (P(x_i) \log P(x_i))$$

Where, X represents Current state, and $P(x_i)$ represents the Probability of event xi of state X.

When the feature importance is tested, the most important features are quantitative aptitude and next was the tenth percentile.

Observation:

The huge overlap of data points is one of the strange findings, which will prove to be a challenge during the model creation process.

2.3.2. Linear regression

Linear regression illustrates the relationship between one dependent variable and one or more independent variables.

The aim of applying regression is to look at two things: (1) Is it possible to predict an outcome (dependent) variable using a collection of predictor variables? (2) Which variables are important predictors of the outcome variable in particular?

Dependent Variable: Quantitative Aptitude Score (From the finding of decision tree)

Observation:

Linear regressions, lasso regressions, and polynomial regressions all failed to estimate accurately, so we can rule out univariate regression models.

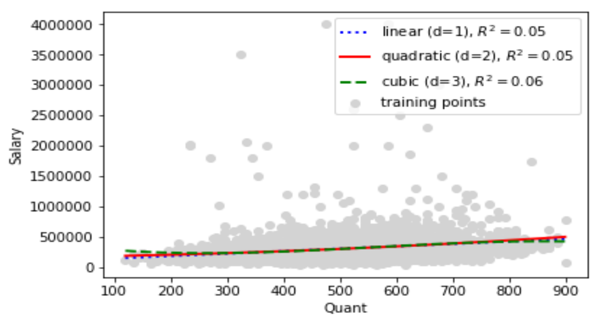

Figure 6. Regression model curve

2.3.3. Single Layer Perceptron Learning

For most of the functions, the pair-plot revealed overlapping datapoints, indicating that the data is non-linear and that we cannot use a single perceptron.

Perceptron equation:

$$y = \sum_{i=1}^{M} x_i w_i + w_o$$

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computed and the weight w_j is updated:

$$w_j^{(k+1)} = w_j^{(k)} + \eta(y_i + \hat{y}_i^{(k)})x_{ij}$$

The perceptron algorithm starts with an initial guess $w_1 = 0$ for the halfspace, and does the following on receiving the example x_i :

Predict $sign(w_i . x)$ as the label for example x_i.

If incorrect, update $w_{i+1} = w_i + l(x_i)x_i$ else $w_{i+1} = w_i$.

In this case, the single perceptron results in incorrect weight updates.

Observation:

The data is not linearly separable hence, single layer perceptron fails to classify the data.

2.3.4. Multilayer Perceptron back propagation Algorithm

For training a MLP model, it needs to adjust different parameters and weighs and bias to minimize the error, it uses backpropagation for adjustments of weights and bias. Difference was observed in result with different activation functions. We have use 4 hidden layers for MLP.

Observation:

By changing the activation function and by changing number of neurons at hidden layer the accuracy of the model changes. (See table 4)

Table 4. Observations for MLP

Hidden layer	**Number of iterations**	**Accuracy**
(4,3,2,1)	1000	27.75%
(4,3,2,1)	5000	25.50%
(7,6,6,4)	6500	31.87%
(6,5,5,3)	5000	31.87%

Since, even with the complex model like ANN the accuracy achieved is 32%. We applied the classification model logic to the dataset.

2.3.5. Logistic Regression

Logistic regression, it is used to predict the categorical outcome. The logistic regression measures the relation between the dependent variable which is categorical and independent variable.

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$$Y = Exp(x) / (1 + Exp(x))$$

$$P = Exp(b0 + b1 * x) / (1 + Exp(b0 + b1 * x))$$

Where, Y is dependent variable; x is independent variable and b0 + b1 * x is a linear predictor.

2.3.6. K-Nearest Neighbor

The KNN algorithm classify the tuples of data into number of groups based of values of certain features in the data. KNN is considered a lazy method, it is easy to implement and understand.

Decide K neighbors → Apply distance measure → identify K closest data point →

Data points count in each group among the K data points → Assign the new data point to the group with the greatest number of neighbors.

Here, KNN is applied, keeping the weights uniform, and applying Euclidean distance as distance measure.

2.3.7. Naïve Bayes

It works on the principles of probability i.e., on Bayes theorem. This algorithm helps predict the class of the unknown data dataset. It applies independence of assumptions between the variable.

$$P(h|D) = \frac{P(D|h)\,P(h)}{P(D)}$$

Where, h is hypothesis of Data D and P(h): prior probability of h; P(D): prior probability; P(h|D): posterior probability; P(D|h): posterior probability.

2.3.8. SVM-Linear

SVM can either be applied for classification or regression function. It follows linear feature combination. SVM aims to find a mathematical hyperplane that separates the data such that related data get falls under same side of the hyperplane.

$$K(x, xi) = sum(x * xi)$$

A linear kernel is a normal dot product of any two given observations.

2.3.9. SVM-RBF

Its structure is same as linear SVM, but this variant has the gaussian kernel. It is used for working with larger datasets. The nonlinear kernel like Radial Basis function kernel, helps create non-linear feature combination, this raises the dimension of data and makes boundary separation more efficient.

$$K(x, xi) = exp(-gamma * sum((x – xi^2))$$

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Where, gamma is a parameter, and 0 <gamma< 1. The default value of gamma=0.1 is thought to be a fair one.

Ensemble Learning:

Ensemble means combining multiple modes together. There are different approaches to achieve ensemble learning.

"Given a dataset of n examples and m features D = {(xi, yi)} (|D| = n, xi ∈ Rm, yi ∈ R), an ensemble learning model φ uses an aggregation function G that aggregates K inducers, {f1, f2, …, fk} towards predicting a single output as follows:

$$\hat{y}i = \varphi(xi) = G(f1, f2, ..., fk)$$

where ŷi ∈ R for regression problems and ŷi ∈ Z for classification problems." [7]

Ensemble approach combines the model to improve the power and accuracy of the model. The performance of this model is higher as compared to single model. We have applied few which has given better results in different problems.

2.3.10. Ensemble-Bagging

It is also called as bootstrap aggregation. It helps in decreasing the variance in the data. For dividing the dataset, it follows row sampling with replacement.

2.3.11. Ensemble-Random Forest

This is a type of ensemble bagging, which combines weak decision trees together and the apply the majority voting mechanism to obtain the outcome.

Ensemble-Boosting

It helps boosting the performance of weak models by combining the together to form a stronger model.

2.3.12. Ensemble-AdaBoost

It is a type of Boosting ensemble approach. This algorithm helps boosting the performance of the decision trees. It is also called as discreate Adaboost because of its application for classification.

2.3.13. Ensemble-GradBoost

It is also a type of boosting ensemble. In this approach the models gradually refine itself by combining with the previous model and minimize the error. It follows the greedy approach and might cause the problem of overfitting.

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2.4. Model Performance Evaluation

For data analytics, pre-processing the standard libraries like Pandas, Scikit Learn, and Numpy are used. The insights and visualizations are generated using Seaborn and Matplotlib. All the work is implemented on jupyter notebooks because this is convenient way to collaborate reproduce and maintain.

Out of 13 Machine learning models developed, we are considering 10 for performance evaluation based on the observations. The measures used for performance evaluation are Accuracy and K-fold cross validation.

2.4.1. Accuracy

The accuracy for the model is also called as error-rate. The percentage of correct predictions for the test data is known as accuracy. It can be determined by dividing the number of correct predictions to the total number of predictions.

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN$$

Where, TP: True Positive; TN : True Negative; FP : False Positive; FN : False Negative.

The comparison of the accuracy for all the classification considered under study is stated in table 5.

Table 5. Accuracy of ML models

SN.	**Classification Model**	**Accuracy**
1.	Logistic Regression	0.786
2.	K Nearest Neighbor	0.716
3.	Naïve Bayes	0.744
4.	SVM Linear	0.796
5.	SVM RBF	0.729
6.	Decision Tree	0.669
7.	Ensemble Bagging	0.745
8.	Ensemble AdaBoost	0.778
9.	Ensemble GradBoost	0.778
10.	Random Forest	0.762

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The accuracy is an easy way to assess your model's efficiency, but it can be deceiving. The accuracy may mislead when we are making prediction of everything as true. When only true values are assigned to the predictors, the accuracy remains high, which is unexpected.

Using Cross-Validation, we can obtain more metrics and draw important conclusions about our algorithm and data. Thus, applying K-fold cross validation for all our models.

2.4.2. K Fold Cross Validation

This validation reveals the model's ability to function with the given data. In this method, we choose a k value and divide the dataset into k units, then each model is trained on k-1 datasets and tested on the remaining one dataset. The algorithm chooses these training and testing datasets at random. This is a well-known statistical technique for estimating and validating machine learning models. All the above models under study were subjected to k-fold cross validation with a k value of 10 and mapped the outcome boxplot as shown in figure 6.

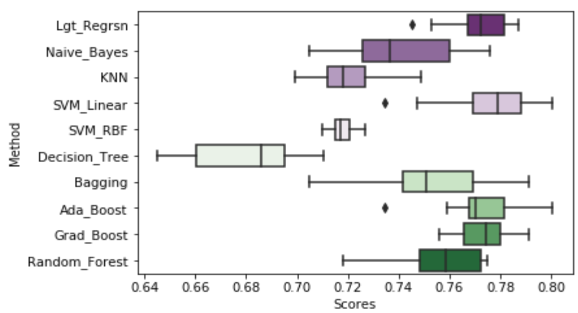

Figure 7. Box plot for 10-fold cross validation

After 10-fold cross validation, the Ensemble approach has the highest accuracy. Amongst ensemble models the accuracy score for the AdaBoost-Ensemble and Gradient Boost-Ensemble models is very high. We can also see from the plot that these approaches show less variance. The decision tree has the lowest level of accuracy. (See figure 7)

3. Result, Discussion and Proposed System

From the previous sections of the paper and accuracy analysis, ensemble learning gives better results compared to the single model approach. In averaging ensemble techniques, the homogeneous models are considered or heterogeneous models with equal weights are considered.

Random forest, for example, is a homogeneous model in which all the poor learners are decision trees. In the above case, the base models for all ensembles are decision trees. All the models considered are assigned the same amount of weight. This method can help minimize variance, but it may lead to increased bias and noise.

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Another approach for ensemble is combining the heterogeneous model together to for a strong classifier. Here, the problem arises if these models are given equal weightage. There might be a base model which gives better prediction and other might give weaker prediction as compared to other, if these models are weighted equally the accuracy might get compromised.

To get better accuracy and prediction it is important that different model in ensemble contribute differently, this can be achieved by applying the weights to the models based upon their prediction accuracy.

The weight is a small positive value which ranges from 0 to 1. The sum of all the weights of the models is 1. The weight indicates the percentage of accuracy of prediction or the trust for that model.

3.1. Proposed Model: Optimization based Weighted Ensemble Learning Prediction Model

The framework of ensemble-based mechanism is inspired from [24] where the author proposed the ensemble learning model with recurrent neural network. The proposed model will consider the heterogeneous ensemble model with weighted average voting for the base classifiers.

In the figure 7, the modelling unit consists of the resampling; it is achieved by applying bootstrapping method for generation of random subsets of the dataset, this is done by row sampling with replacement approach.

The sub-sample of dataset is of size say, m where $m<N$ (N is the size of complete dataset). These sub-sampled datasets are given to the base classifiers. These classifiers generate the prediction for each output class.

As discussed in the previous sections applying equal weight average would result in suppressing some good predictions, thus, to overcome this optimized weighted average approach is used. This unit will generate the adjusted and optimized weight for each classifier and each output class. Based on these weights the further ensemble voting will take place and thus the final prediction will be made.

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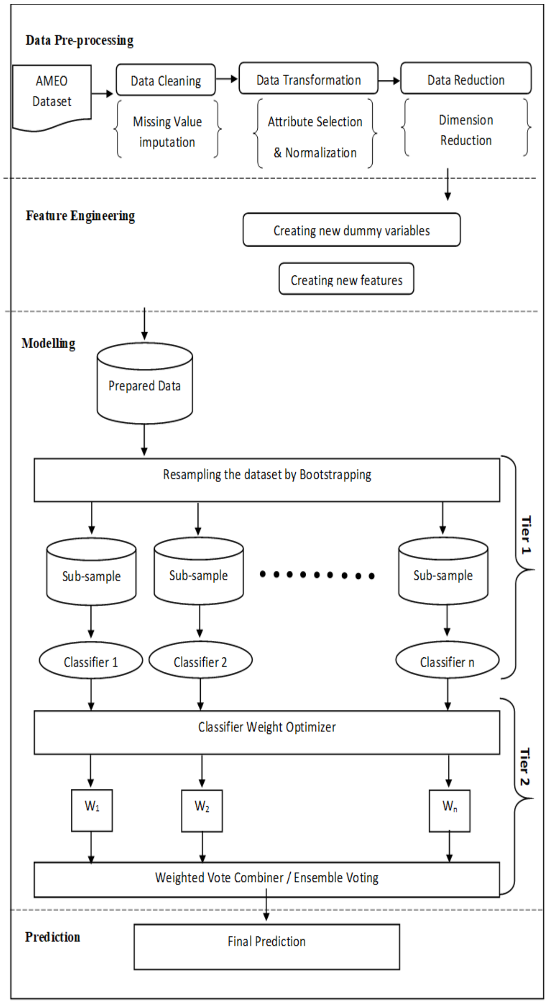

Figure 7. Optimization based Weighted Ensemble Learning Prediction Model (Proposed System)

4. Conclusion and Future Work

In this paper different machine learning algorithms along with ensemble models are trained over the AMEO 2015 dataset. Using k-fold cross validation, all of these algorithms were compared for accuracy, and it was discovered that ensemble learning models produced better results. Based on the same finding the optimization-based ensemble learning approach is proposed for predicting the employability and job readiness of the engineering students in India. The following hypothesis is framed based on proposed system.

Hypothesis Defined

H0: The current classifier models and the proposed novel Optimization based Weighted Ensemble Learning prediction model have the same accuracy.

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HA: The proposed novel Optimization based Weighted Ensemble Learning prediction model outperforms the current classifier models by a significant margin.

In subsequent papers, we will go through the optimized weighted ensemble model in greater depth, as well as a comparison of various optimization mechanisms for determining the weights for each classifier. In addition, the proposed model will be tested against the specified hypothesis on the dataset.

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