IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Student Academic Records Mining & Performance Prediction Using DT-J48 Algorithms

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Abstract - **Automatic Student overall performance prediction is a vital job due to the giant extent of statistics in instructional databases. This job is being addressed by means of academic records mining (ARM). ARM increase strategies for discovering statistics that is derived from academic environment. These techniques are used for grasp scholar and their gaining knowledge of environment. The academic establishments are frequently curious that how many college students will be pass/fail for indispensable arrangements. In preceding studies, it has been found that many researchers have intension on the resolution of gorgeous algorithm for simply classification and ignores the options of the issues which comes all through facts mining phases such as statistics excessive dimensionality, category imbalance and classification error etc. Such sorts of troubles decreased the accuracy of the model. Several universal classification algorithms are utilized in this area however this paper proposed a pupil overall performance prediction mannequin based totally on supervised studying choice tree classifier. In addition, an ensemble approach is utilized to enhance the overall performance of the classifier. Ensemble techniques strategy is designed to clear up classification, prediction problems. This find out about proves the significance of statistics preprocessing and algorithms fine-tuning duties to get to the bottom of the facts high-quality issues. The experimental dataset used is acquired from UCI Machine Learning Repository. Supervised mastering algorithms Decision Tree (J48) are employed in this find out about for experimental purposes. The effects confirmed that J48 performed absolute best accuracy 95.78% amongst others.**

Keywords— Educational Data mining, Educational Data Mining, Predicting Student Performance, Decision Tree, Ensemble

I. INTRODUCTION

Educational fine is obligatory in the improvement of every country. The records quantity in training area is getting expand day by means of day with the assist of admission system, educational statistics system, studying administration system, e-learning etc. The records accumulated from college students are normally used for making easy quires for choice making. But most of the statistics stay unused due to complexity and massive quantity statistics sets. Therefore, to analyze this big quantity of academic information is the high-quality pastime to predict pupil performance. Data mining is the exercise of discover out beneficial data from big units of data, additionally recognized as know-how discovery in databases (KDD). It has been utilized efficiently in more than one domain together with banking, medical, enterprise and now has been used for academic functions referred to as Educational Data Mining.

The prediction of scholar overall performance is a fundamental assignment which is being researched by using the usage of ARM. This assignment foresees the price of an unidentified variable which describes the college students involving result (Pass/Fail), grades, marks etc. Predicting scholar Attrition, failures, success are the predominant areas which are mentioned in the literature evaluation of this study. Each stakeholder belongs to this area needs an early warning device to predict gaining knowledge of on early stages. This early warning gadget no longer only decreased the gaining knowledge of prices however additionally time and house requirements.

One of the largest challenges is to enhance the satisfactory of the instructional methods to decorate student's performance. Instructors can replace their instructing methodology to fulfill the requirement of negative overall performance college students and can furnish extra training to deserving students. The prediction effects would possibly assist college students improve a right appreciation of how nicely or horrific they would function in a path and then can take steps accordingly. Increasing the pupil retention is a long-term goal of any instructional establishments round the globe. There are many nice affects of elevated retention such as elevated university reputation, rating and higher job possibilities for alumni etc.

To analyze information the use of classification technique, nicely recognized classification algorithms such as Decision tree (DT), Artificial neural networks (ANN), K-neatest neighbor (KNN) and Rule Induction (RI) are being used for prediction purposes. Quality of a predictive classification mannequin is measured by means of its capacity to locate out the unknown patterns accurately. This learn about employed three classification algorithms J48 from DT, NNge from IR and MLP from ANN for experimental purposes. The fundamental goal of the proposed methodology is to construct the ensemble classification mannequin that classifies a students' overall performance as Pass or Fail.

II. PREVIOUS WORK

Dorina et al. [1] proposed a predictive mannequin for student's overall performance by way of classifying college students into binary category (successful / unsuccessful). The proposed mannequin used to be built beneath the CRISP-DM (Cross Industry Standard Process for Data Mining) re-search approach. The classification algorithms (OneR, J48, MLP and IBK) had been utilized on the given dataset. The consequences exhibit that the easiest accuracy was once performed with the aid of the MPL mannequin (73.59%) for identification of profitable whilst different three fashions per-form higher for the identification of unsuccessful students. The mannequin used to be unable to work out for records excessive dimensionality and classification balancing problems.

Edin Osmanbegovicet al. [2] builds a mannequin to predict scholar educational success in a direction by using lowering facts dimensionality problem. Various desktop studying classifiers such as NB, MLP and j48 had been evaluated in this study. The result suggests that the Naïve Bayes received the perfect accuracy 76.65%. The proposed mannequin now not handles the category imbalance problem.

Carlos et al. [3] addressed a pupil failure prediction mannequin based totally on laptop studying methods to unravel the category imbalance and statistics dimensionality problems. Ten classifiers have been utilized on dataset. The ICRM classifier accomplished the very best accuracy 92.7% amongst others. Due to various student's traits at every instructional level, the overall performance of proposed mannequin was once no longer examined for different stages of education.

Another ARM Challenge is to predict the dropouts of the college students from their guides [4]. Four records mining strategies with six combos of attributes had been participated in this study. The result suggests that the guide vector desktop mannequin with the aggregate of the predictor variables used to be greater correct whilst classifying the data. The inclusion of an attribute, earned grades of pre-requisite guides in the information set was once the hassle of this learn about due to the fact it would possibly be feasible that for the duration of find out about of any direction the pupil would possibly have increased his information of pre-requisite of this course.

Ajay et al. [5] performed find out about on the prediction of scholar performance. The foremost contribution of the learn about used to be to introduce a new social thing referred to as "CAT" which de-scribes that in early instances Indians had been divided into 4 kinds of companies on the groundwork of their social reputation etc, which have a direct impact on the scholar education. Four classifiers oneR, MLP, J48, and IB1 had been utilized on the information set. The effects indicated that the IBI mannequin used to be the absolute best accuracy (82%) achieved.

Build an extended model of the ID3 model, which predicts the pupil tutorial overall performance [6]. The weak spot of the ID3 mannequin used to be its intension to pick these at-tributes as a node which had greater values. In a end result generated tree used to be now not efficient. The proposed mannequin overcomes such problem. Two output lessons had been produced with the aid of this mannequin (Pass and Fail). The classifiers along with J48, wID3 and Naïve Bayes have been utilized and effects compared. The wID3 finished excessive accuracy 93%.

Alaa Khalaf et al. [7] proposed a mannequin to predict scholar success overall performance in courses. Three Decision Tree classifiers such as (J48, Hoeding tree, Reptree) have been employed by means of this study. The very best accuracy 91.47 percent used to be done with the aid of Reptree. The mannequin used to be unable to work out for facts excessive dimensionality and classification balancing problems.

Dech Thammasiri et al. [8] proposed a mannequin to grant early classification of terrible educational overall performance of freshmen. Four classification techniques with three balancing techniques have been utilized to unravel type imbalance problem. In effects the aggregate of aid vector laptop and SMOTE executed the 90.24% very best normal accuracy.

An early warning gadget was once proposed to predict the pupil getting to know performances throughout an online route based totally on their studying portfolios information [9]. The outcomes confirmed the tactics accompanied via time structured variables had excessive accuracy than different methods which have been now not protected it. The mannequin was once now not examined on offline mode. The overall performance may be reduced in offline mode the use of time established attributes.

Mostly preceding research have been assumed that the facts mining algorithms carried out nicely with solely giant facts units however this find out about supported that the information mining is additionally suit-able for small datasets as properly [10]. This lookup proposed a scholar success prediction model. A small dataset which include pupil tutorial information was once used through the use of three selection tree strategies (Reptree, J48, M5P). The end result claims that the Reptree bought the absolute best accuracy above 90% amongst them. The proposed mannequin now not supported to facts excessive dimensionality and type balancing problems.

Camilo et al. [11] proposed a mannequin to predict scholar educational attrition by using over-coming classification imbalance problem. Two algorithms Naïve Bays and Decision tree had been used with the aid of this study. A cost-sensitive approach. Metacost used to be used to control this problem. After that best possible accuracy was once acquired through navieybays upto 85%. The facts series at the quit of educational length is no longer viable due to the fact no one can get gain at that time.

A student educational overall performance prediction mannequin was once proposed in this learn about [12]. The classifiers specifically J48, Decision Stump, Reptree, NB and ANN with three sorts of attribute setups have been evaluated in this study. The J48 classifier finished the excessive accuracy 90.51%.

Proposed approached was once contributed with the aid of evaluated three wide variety of lessons (drop-out, persisting, and completed) whilst predicting scholar dropout [13]. Ten classification fashions have been assessed. The effects of experiments depict that the Naïve Bayes algorithm had the perfect predicting stages for the three training of students.

Bilal et al. [14] introduced a scholar failure prediction mannequin which recognized the college students that may be at-risk. Four output training (Average, Risk, beneath Average and Above Average) have been generated via the proposed mannequin based totally on the CGPA of the students. Six classifiers along with had been utilized on the given dataset. The ID3 acquired the absolute best accuracy 79.23%. The mannequin was once unable to work out for classification imbalance problem.

An ensemble mannequin which include classifiers (NB, SVM, KNN) was once proposed for the identification of susceptible college students [15]. The dataset protected a most high-quality attribute as general based totally grading evaluation in addition to common score-based grading. The consequences of proposed mannequin with six different man or woman classifiers had been in contrast and conclude that the accuracy of ensemble mannequin used to be 85% which is greater than others.

A multilevel classification mannequin used to be proposed to get to the bottom of the multiclass classification trouble in the prediction of scholar overall performance [17]. The aim of learn about used to be now not solely to extend the mannequin accuracy however additionally extend the accuracy of the man or woman classifier. The mannequin carries two levels. Initially a re-sampling method used to be per-formed on the dataset to overcome the classification distribution trouble in the preprocessing phase. In the first level, 4 classification fashions have been utilized on the dataset particularly

IBK, MLP, NB, J48. Results had been evaluated and compared. The outcomes exhibit that the choice classifier (j48) was once relatively correct and chosen for use in the subsequent level. In the stage two, outliers had been recognized via evaluating the until now anticipated consequences with genuine effects and eliminated accordingly. Once once more re-sampling approach with excessive correct classifier which used to be chosen preceding (J48) was once utilized onto the filtered dataset and outcomes had been in contrast with the consequences of making use of closing classifiers additionally on the filtered dataset. The outcomes depict that the J48 classifier bought the above 90% accuracy for general mannequin as nicely as for character lessons prediction.

An early pupil failure identification mannequin used to be proposed in this learn about through evaluating records mining methods as nicely as preprocessing approaches. Several methods and fashions had been utilized (ANNs, selection trees, assist vector machines, naïve bayes) in this learn about and conclude that the aid vector machines is outperformed from the others ones [18]. The facts was once amassed from two exclusive kinds of information sources. Model now not supported for lowering the classification errors.

III. METHODOLOGY

A general framework of Educational Systems and the relation of Data Mining with it is that it combines various category of data of students into a single frame of dataset. And then, various inevitable processes of Data Mining being applied to excavate hidden knowledge about students. A similar one is illustrated in the figure (Fig. 2). Most of the system have different combination of mining and reporting facilities to come across suitable decisions. The point of uncertainty of indirect information, is cleared while using data mining rather than normal querying. Selection of methods is decided, based on the problem it has to address.

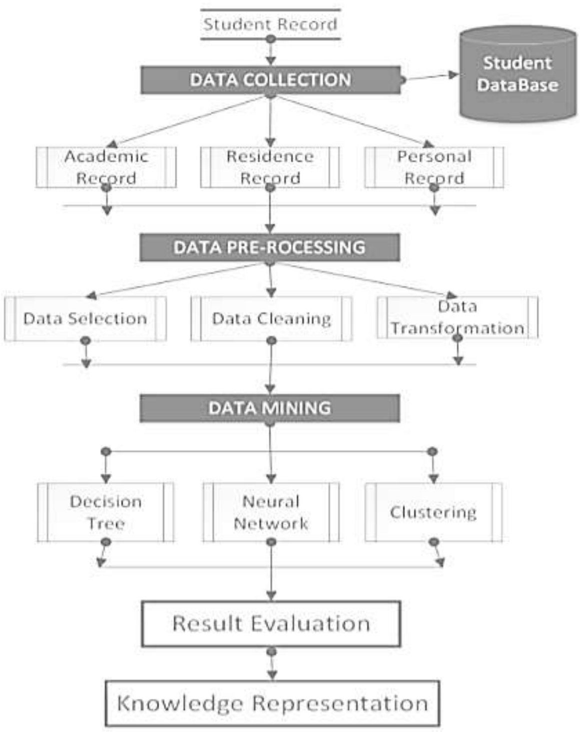

Figure 4.1 Proposed System for Student Academic Performance prediction

Data collection A pupil overall performance information set used in this learn about has accumulated from UCI Machine Learning Repository [16]. The information was once gathered for educational session 2005-2006 of two colleges of Alentejo vicinity Portugal. It includes 1044 situations with 33 attributes which includes scholar grades, demographic, social and faculty associated features.

Data preprocessing Pre-processing performs an essential in records mining. Its cause is to convert uncooked information into a appropriate shape which can be used by using mining algorithms. Following duties are per-formed in this phase.

Data integration: Data Integration capability to acquire the information from the a couple of sources into single repository. Redundancy is the frequent trouble took place when integrating data. The dataset consists of two comma separated values documents which had been taken from UCI Machine studying repository.

Data cleaning: In this phase, lacking and noisy facts is dealt with to gain information consistency. The dataset occupied by way of this find out about now not have any lacking and outliers etc.

Feature selection The scholar overall performance dataset may additionally comprise many attributes, which can also be inappropriate for classification purposes. The hassle of records excessive dimensionality arises when blanketed giant quantities of student's traits which can affect scholar overall performance such as academic background, social, demographics, family, socioeconomic popularity etc. This trouble can be unravel by means of choosing vital elements from the dataset.

Proposed framework of classifier evaluation

The specific student experimental model is designed for predicting the outcome of students by the classifiers including the base classifier ZeroR. The other classifiers of the interest are DT (tuned J48). The basic framework of implementation is given below in Figure (Fig. 4.2). Data are the two similar datasets used here. Data preparation is being followed required file processing. The framework proposed have a core stage where basic checks were done and the datasets were prepared using 10Fold Cross Validation and Percentage Split before, pre-processing, and selection. Data get transformed to train and test data. Later these data were pre-processed, attributes are selected and given data for classification with various analysis based on a set standard condition. Base classifications and classifications with probabilistic, frequency table, associated learning, neural network and ensemble models have been considered and evaluated. This will give an efficient analysis on student prediction accuracy and help to compare them individually. The results of Model were taken and compared.

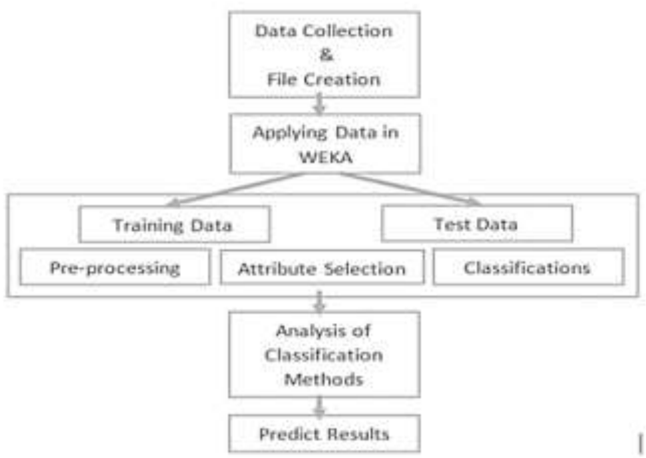

Figure: Framework of Classifier Evaluation

A specific model with tuned J48, the best performing model to predict and give better accuracy can be found from these analyses. It will help SNG stakeholders to take a better managerial decision on educational service and students can correct themselves using these results.

Decision Trees techniques

A decision tree is a hierarchical structure that depicts the classification of a dataset into groups. As in any classification problem, the goal here is to build a model that predicts the values of a variable given the values of other variables. Decision trees follow a supervised learning approach, training a model based on a sample of known observations as input and known responses as outputs. The tree structure results from the recursive splitting of the root node, which contains all training dataset, according to simple rules of the type xi ≤ d, where xi is the value of an independent variable (or attribute) and d is a real number. In each step of the top-down greedy search, a variable is selected to separate the data of the node, based on the information gain criterion, i.e. how homogeneous (pure) would be the data included in the child nodes. The splitting continues until a leaf node (or end node) is reached, in which predetermined purity or stopping rules have been met. These stopping criteria can be tight or loose, creating small and under-fitted or large and over-fitted trees. Several pruning methods have been invented to allow trees to overfit the training dataset and then reduce their size, removing sub-trees that increase complexity and reduce generalization accuracy [22].

Given a training dataset {(xi , yi): i = 1, 2, … , n} – where xi is the k-dimensional input vector (x1, x2, … , xk) of the independent variables, yi is the class output taking values in {1, 2, … , m} and n is the number of observations – different algorithms can be used to split the data records in subsets based on the association of each input variable xj (j = 1, 2, … , k) with yi . The ID3 (or Iterative Dichotomiser 3) is a very simple algorithm that uses Shannon Entropy function to grow a multiway decision tree, as long as the information gain is greater than zero. It applies only to categorical data and creates complex trees that tend to over-fit training data. C4.5 algorithm is the evolution of ID3 and applies to both categorical and numerical attributes. It also uses Shannon Entropy to choose the attribute that maximizes the information gain, but, moreover, uses bottom-up pruning and handles missing data [23]. CART (Classification and Regression Trees) algorithm is similar to C4.5, but constructs only binary trees and uses Gini Impurity to select the best attribute for splitting the dataset. Besides from handing both categorical and continuous attributes, CART can also create regression trees and predict not only the class but the absolute value of the dependent variable.

```
Tree growing algorithm growingtree(X, A, y)
  Input    Training dataset X, attribute set A, output variable y
  Output   Decision tree
Begin a single tree T with a root node
If all stopping criteria have been met then
  | T has one node with the most common class in X as label
else
  | find a ∈ A, that best splits X using impurity function
  | Label node with a
  | for possible value v of a do
  |   | X = the subset of X that have v = a
  |   | A = attribute set A – the best split attribute a
  |   | growingtree (X, A, y)
  |   | connect the new node to the root node with label v
return pruningtree(X, A, y)
```

Figure 4: tree growing algorithm pseudocode

Figure 5: Tree pruning algorithm pseudocode

```
Tree pruning algorithm pruningtree(X, A, y)
  Input    Training dataset X, attribute set A, output variable y
  Output   The pruned tree
T_1 = T(0)
a_1 = 0
k = 1
while T_k has at least 1 node do
  | for all non-terminal nodes t ∈ T_k
  |     g_k(T) = (R(T) − R(T_{k,t})) / (L(T_{k,t}) − 1)
  | a_{k+1} = min_t g_k(t)
  | when g_k(t) = a_{k+1} prune at t to obtain T_{k+1}
  | k = k + 1
```

Figure 5: Tree pruning algorithm pseudocode

In order to split the data, CART uses the Gini index of node impurity. At node t the Gini index is defined as

$$Gini(t) = 1 - \sum_{j=0}^{1} \left[\frac{n(j/t)}{n(t)}\right]^2$$

where j is a class of target variable (in this study j = 0 means failure and j = 1 denotes success), n(j | t) is the number of records of node t belonging to class j, and n(t) is the total record number in node t . When the data in a node are equally distributed between all classes, the Gini index attains its maximum impurity value 0.5. In the case where all data belong to the same class, the node has minimum impurity and Gini index is 0. In order to decide which attribute to split upon, the tree growing algorithm calculates the weighted average of the Gini index for the descended nodes

$$Gini(t)_{split} = \frac{n(t_L)}{n(t)} Gini(t_L) + \frac{n(t_R)}{n(t)} Gini(t_R)$$

As can be seen the classification results tabulated and shown in Figure 8, the CART model correctly classified 167 students who were failed the course, but misclassified 3 where tL and tR are the left and right child nodes of node t . The attribute that minimizes the Gini(t)split is chosen to split the node.

IV. RESULTS AND DISCUSSION

4.1 Model evaluation

For our experiments, three classifiers J48 have evaluated using 10-folds cross validation technique. This technique divides the data set into 10 subsets of equal size; nine of the subsets are used for training, while one is left out and used for testing. The process is iterated for ten times, the final result is estimated as the average error rate on test examples.

4.2 Evaluation measures

In our experiments, we use five common different measures for the evaluation of the classification quality. Details are under as:

- **CCI (Correctly Classified Instances): represents** the number of correctly classified instances divided by the total instances. It is also known as accuracy.
  The CCI formula is= (TP+TN)/(TP+FP+TN+FN)
- **ICI (Incorrectly Classified Instances):** represents the number of incorrectly classified instances divided by the total instances

The ICI formula is= (FP+FN)/ (TP+FP+TN+FN)

- **Precision:** of algorithm represents the percentage of accurate classified instances from all truly classified instances.
  Precision = TP/TP+ FP

- **Recall:** reflects the division number of correctly classified instances by the total number of all instances (almost recall value be same as CCI).
  TP rate= TP/TP+FN

- **F-Measure:** measured from recall and precision values (double value of precision multiplied by recall divided by the value of summation of recall and precision).

4.3 Result analysis

In the first experiment, three classification algorithms (J48) are honestly performed for my part on dataset besides the use of proposed mannequin steps. In the mild of consequences noted in Table two and graphical illustration of parent 3, it has been found that the best possible accuracy carried out by way of J48 which is now not ample as com-pared to preceding research and lowest accuracy has done via MLP.

Table 2. Classification Method Results with original dataset

Algorithm	CCI	ICI	Precision	Recall	F-Measure
J48	78.78 %	77.21 %	70.958	75.958	73.958

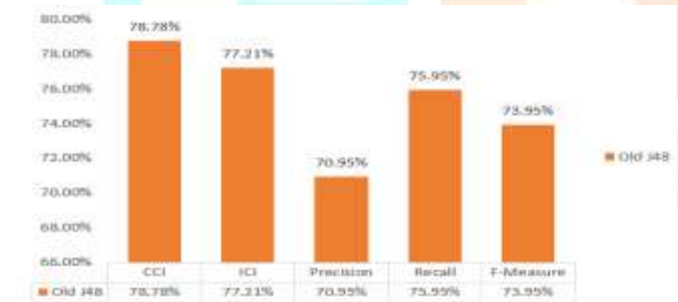

Fig. 3. Previous Model Performance Measures

In the 2nd experiment, proposed methodology has performed step by using step. Results can be considered in desk three with graphical illustration in determine four It has been ob-served that the best accuracy executed is 95.78% by using J48 classifier and the lowest accuracy executed 92.81% via NNge. It has found that after lowering category imbalance, statistics excessive dimensionality as nicely as through the use of ensemble approach the proposed mannequin accuracy has increased drastically for all classifiers.

Table 3. Results of proposed Model

Algorithm	CCI	ICI	Precision	Recall	F-Measure
Previous Algorithm	78.78 %	77.21 %	70.958	75.958	73.958
Proposed Algorithm	92.81 %	96.18 %	90.929	95.928	94.928

Fig. 4. Proposed Model Performance Measures

During this experiment, we have additionally measured the classification blunders in phrases of Root Mean Squared Error (RMSE). Figure 5 indicates the graphical illustration of RMSE. This without a doubt suggests the effects with and besides ensemble classification blunders rates.

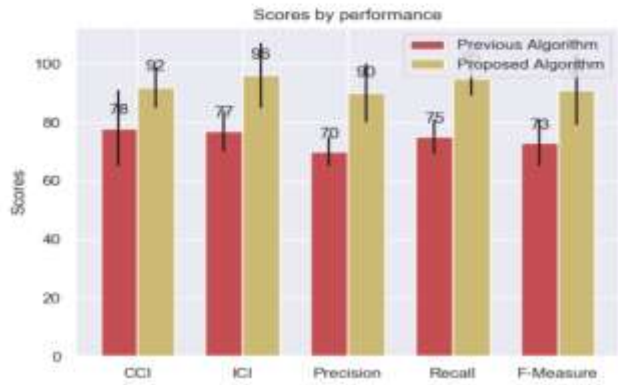

Fig. 5. RMSE of single and Proposed Model Comparison

4.4 Model comparison

In this part we in contrast the consequences of different pupil overall performance prediction mannequin with our proposed system. Table four suggests the element of participated techniques such as SVM, Decision Stump, Reptree and Our proposed ensemble approach with their carried out actions. Our proposed mannequin carried out all the moves such as classification balancing, characteristic determination and use of ensemble methods. The effects exhibit that our proposed find out about has an improvement, being greater than others in phrases of accuracy.

Table 4. Comparison of Proposed Model with other Techniques

Technique	Data source	Data set	Class Balancing	Feature Selection	Ensemble Method	Results of Reference study
SVM	Tulsa, USA	2165	Handled	Handled	Not Used	90.32%
Decision Stump	UCI Student Performance	649	Not Handled	Handled	Not Used	90.51%
Reptree	UCI Student Performance	1044	Not Handled	Not Handled	Not Used	91.47%

Ensemble (J48, Realadaboost)	UCI Student Performance	1044	Handled	Handled	Used	95.78 %

V. CONCLUSION

The correct student educational overall performance prediction mannequin is demand of each and every instructional institute nowadays. But to unravel the records best problems in pupil overall performance prediction mannequin is regularly largest challenge. This lookup work, introduced a scholar overall performance prediction mannequin based totally on supervised mastering method Decision Tree. The overall performance of Student's predictive mannequin is assessed on dataset by using set of classifiers namely; J48. In addition, an ensemble technique is utilized to enhance the overall performance of these classifiers. The end result suggests that the proposed ensemble mannequin which include Decision tree (J48) classifier completed the excessive accuracy which is 95.78 %.

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