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Decision Support System for Prediction of Student Academic Performance

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Abstract
Over the years, data mining has been successfully adopted to transform the business world by implementing different models for evaluating business performance. Analyzing and evaluating large volume of dataset by these data mining models keeps its application growing wide. Several data generated from student academic results and bio data calls for a need to create knowledge out of the data set. Students' academic performance evaluation is a necessity and incredibly challenging, and thus, is intended for identifying and extracting new and potentially valuable and actionable knowledge from the data. It is a complex research undertaking to identify and indicate the issues harming students' academic performance. Performance prediction models can be built by applying machine learning tools to enrolment data. This paper presents five Machine Learning models- K-Nearest Neighbour Classifier, Random Forest, Gaussian Naïve Baye's Classifier, Decision Tree, and Support Vector Classifier- for predicting students' continuous performance and graduating cumulative Grade Point Average. Each model is applied to data set on the enrolment data and examination results for three different academic sessions ranging from the first year to the graduating year. The comparative analysis of the performance of each of these models is carried out based on accuracy of prediction.

Keywords*: Decision Support system, Machine Learning, Academic Performance, Student enrolment data, mode of residence.*

1.0 Introduction

Several Higher institutions contribute to improve students' academic performance in higher Institution by continuous monitoring and evaluation of individual performance over a given period of time which could either be a semester or a session. The main focus of admission processes is to determine the candidates who would likely perform well after being accepted into the university. Since the quality of the teaching process is usually measured by the general performance of the students, it is essential to have a standard model for evaluating individual student performance and thereafter their overall performance. Therefore, the prediction of students' success is essential for higher education and Technical education institutions, because the quality of teaching process is measured by the ability to meet students' needs. In this vein, important data and information are gathered on a regular basis, and they are considered by the appropriate authorities and standards in order to maintain the quality of their decisions. Most researchers in academics could benefit from several available tools in making concrete analysis by applying data mining models on the data from the higher education system.

Educational data mining is implicated with evolving, investigating, and relating computerized methods to discover arrays in big assemblies of educational information. This also described the presentation of data mining techniques to data sets derived from educational settings that could point to significant educational problems. Thus, focuses on gathering, achieving, and studying of information concerning student's assessment and learning for better decision making, and to improve the quality of the teaching process [15]. Most researchers in academics could benefit from several available tools in making

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concrete analysis by applying data mining models.

Building a performance prediction system can be achieved by applying different data mining models in order to make meanings out of the available data set. Students' results containing both bio data and graduation grade points are usually kept in a separate database by various higher institutions, thus, enabling them to keep track of both the current and past record of students that graduated from each of the department in an institution. These data are being generated every semester by various departments in the institution, which makes it necessary to make meaning from it and as well as to presenting a support for quality decision making.

Universities have been using many Machine Learning techniques to analyze educational report stored in the institutional repositories or databases, such as enrolment data, students' performance, teachers' evaluations, gender differences, and many others. For an instance, Machine Learning (ML) techniques accord a university the much needed information for better planning students' enrolment number, drop out, early identification of weak students, and to efficiently allocate resources with a precise approximation. Building Decision support systems (DSS) driven by ML will help advisors instruct students in choosing suitable courses and appropriate study plans. Thus, this paper aims at the development and evaluation of a DSS for prediction of students' academic performance based on five ML models using a typical University Undergraduate programme as a case study.

2.0 Related Works

Several researchers have conducted studies on students' academic performances and so many others have carried out a scholarly research on prediction of academic performance of students [1]. Previous studies have investigated average grades, length of study and similar indicators for determining success of studying at higher institution of learning, while factors affecting student result achievement in a particular course have not been sufficiently explored. This paper conceptualizes different data mining techniques suitable for classifications to fill the gaps and evaluates the results of the generated models.

Performance may be seen as quantifiable conduct of human or animal in a certain environment or situations. It is a yardstick to identify slow learners amongst students in order to create a suitable environment for them [1][11][16]. Students' academic performance is not only an accreditation and evaluation criterion, but it is also at the heart of the institution's contribution to successfully prepare the next generation for the future ahead [17].

Intelligent DSS and Application had influenced remarkable advances in decision making tool using Artificial Intelligence method. They are developed to mimic the human like decision making via an expert system [2]. Typically, decision support system assists decision-makers in manipulating data and models. And plays not an intelligent assistant's role to the decision maker. Recently, Intelligent DSS has gained increasingly significance in the DSS field, with the inclusion of artificial intelligence techniques and methods, as for example: knowledge bases, fuzzy logic, multi-agent systems, recommendation systems, natural language, genetic algorithms, neural networks and so forth.

Khan *et. al.* [9] applied eleven machine learning algorithms to predict student performance in introductory programming language using WEKA. In their findings, Decision Tree (J48) gave a better accuracy in predicting the performance of the student in introductory programming language in terms of correctly identified instances, true positive detection and F-measure rate.

Mohammadi *et. al.* [14] also predict student academic performance using KNN, DT and Naïve Bayes classifiers on the dataset of 230 students of Kabul University to predict their CGPA as high, medium and low. Machine Learning algorithm and ensemble methods has been extensively explored for prediction and classification of student academic performance.

VeeraManickam *et. al*. [19] proposed a Map-reduce architecture based cumulative dragonfly based neural network (CDF-NN). In this method, a neural network is being trained on cumulative dragonfly algorithm with student mark collected from 1 to 7 semesters in various colleges. The proposed model outperform the existing Neural Network model such as Dragonfly- NN and Back prorogation algorithm for student academic performance prediction with MSE of 16.944 and RMSE of 4.665.

3.0 Methodology

The dataset used for the decision support system was gathered through consultation of related works, collection of past records of University of Ibadan students' admission and procedures, as well as, the corresponding academic performances of selected samples over the years. Various classification models are applied in this work and the implementation tool is Python.

Series of data preparation and preprocessing operations were carried out on the dataset, such as feature extractions, dimensionality reduction, feature scaling, string and categorical feature encoding and removal of co-linearity among features. Several data visualisations such as scatter plot, box plot and histogram were employed to have a better understanding of the dataset before the actual modelling. Five Machine Learning models- K-Nearest Neighbour Classifier, Random Forest, Gaussian Naïve Baye's Classifier, Support Vector Classifier, and Decision Tree- are built for predicting students' performance sample. These models were used in order to have a comparative analysis of the results obtained with a view to choosing the model that best fits the trend of the dataset for optimum prediction.

3.1 General Model

Machine learning helps us find patterns in data which could be used to make predictions about new data points. Hence, the data set must be constructed and correctly transformed in order to make right predictions. Figure 1 illustrates the general machine learning pipeline. It consist of input data, random sampling of data, training and testing dataset, machine learning algorithm for prediction or classification and the actual prediction or output.

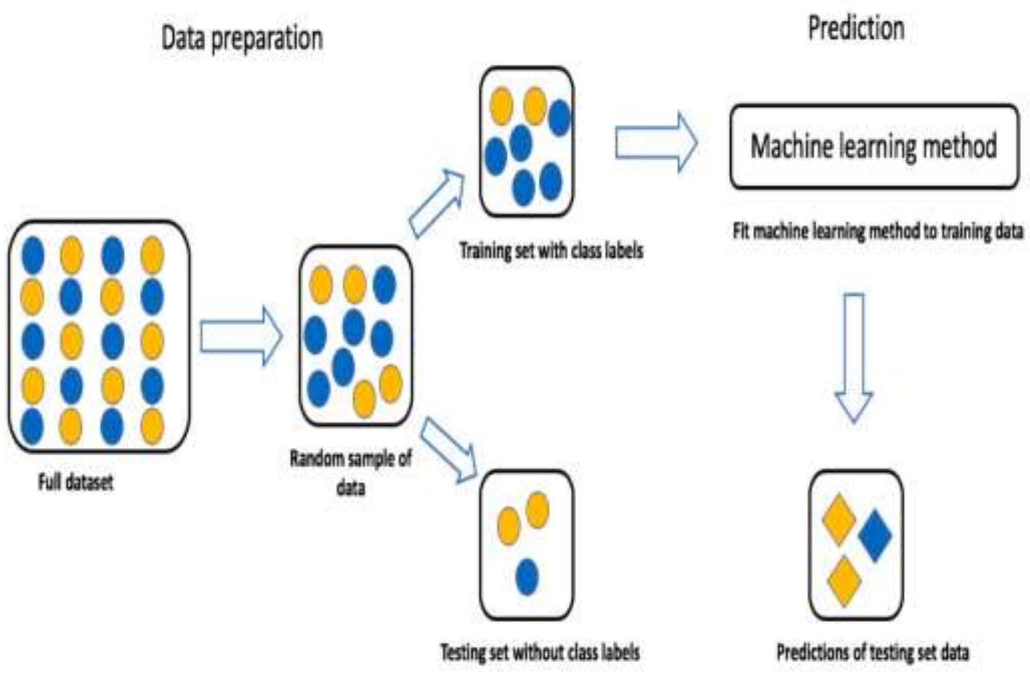

Figure 1: General Model of Machine Learning Model [8]

3.2 Model Building

The model was implemented using Python programming language, in Jupyter Notebook of Anaconda Distribution IDE. The following stages were involved in the building process.

3.2.1 Data Acquisition Stage

The data set used in this research was obtained from the Department of Computer Science, University of Ibadan, Ibadan, Oyo State, Nigeria, for the academic year of 2013 to 2016. The dataset consists of 220 records of undergraduate students who was admitted to he department through Direct Entry (DE) and Unified Tertiary Matriculation Examination (**UTME**) It was subjected to data cleaning and preprocessing.

3.2.2 Data Cleaning and Exploration Stage

This stage involves merging of data from different sessions adding "session" field for identity, removing inconsistencies in headings, values, and removing redundancies and incomplete records. Also, format mismatch among the datasets was resolved. Then, the datasets were imported into IPython Notebook environment for further analysis and Data preprocessing using "pandas" series. Further exploration of the dataset aids the discovery of more anomalies.

3.2.3 Data Formatting Stage

Inconsistencies in the values of data items was corrected; for instance, for STATE field, some values contain "Lagos" others "Lagos State". Misspelt words were also corrected. Correction of the inconsistencies results to the dataset in a consistent state.

3.2.4 Data Quality Improvement Stage

The data quality was improved by filling in missing values, using the mode, median or mean of all other values, depending on the kind of data. Some extreme values, such as a date of birth with year 1900.

3.2.5 Exploratory Data Analysis

The data was analyzed for better understanding, using various data visualisation techniques such as scatter plot, histogram and box plot.

3.2.6 Feature Engineering

Features such as Age was extracted from Date of Birth and features that would not contribute to the prediction process such as S_No, Names, Matric No, and others (dimensionality reduction) was removed. Categorical string features were encoded into numerical features or numbers (label encoding) and features with more than two categories, converted to separate feature (One-Hot Encoding) using pandas get_dummies() function. And finally removed the first feature of each one-hot encoded category to reduce multicollinearity in the data. The dataset was scaled to reduce the mean () to zero (0) and standard deviation to one (1), this is necessary to ensure models that depend on distance measurement such as KNN and even DT and RND Forest to perform optimally.

3.2.7 Splitting the Dataset:

The dataset was splitted into (80%) training set and (20%) evaluation set using the train_test_split function of the sklearn.model_selection class from the python sklearn library.

3.2.8 Training the Models:

GridSearchCV class was used to tune parameters for optimum performance of some of the models whose performances can be greatly improved by tuning their parameters, such as, KNN, Random Forest and SVC, and then trained (fitted) the five models with the training set. Figure 2 shows the architecture of the prediction model used in this paper.

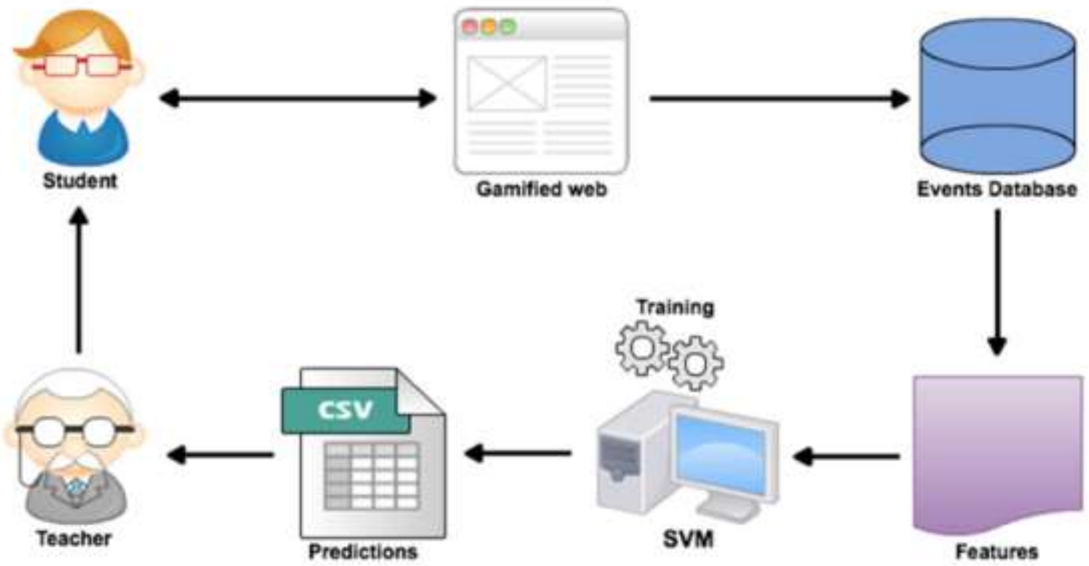

Figure 2: The architecture of the Machine Learning Prediction Model [Adapted from 17]

4.0 Results and Discussion

The implementation was done with Python (version 3.5) programming language using Jupyter Notebook of Anaconda Distribution Integrated Development Environment (IDE) (version 3-5.2.0.). It was run on an Intel(R) Core(TM) i5-2540M CPU @ 2.60 GHz 2.60 GHz Sytem with 4.00 GB RAM, 64-bit Windows 10 Operating System. Figures 3, 4 and 5 depict the visual analysis of the academic performance of three sets of enrolled students based on mode of entry (UTME or DE) while figures 6 and 7 analyze the performance based on residence type (hostel/resident or off-campus/non-resident). The general outcome of the models affirms that the DE and/or resident students have better academic performance in comparison with the UTME and/or non-resident students. In order to buttress this result, figure 8 evaluates the general performance for all modes of entry, which shows that DE students have a better performance. Lastly, in figures 9 and 10, the performance of each mode per session was evaluated.

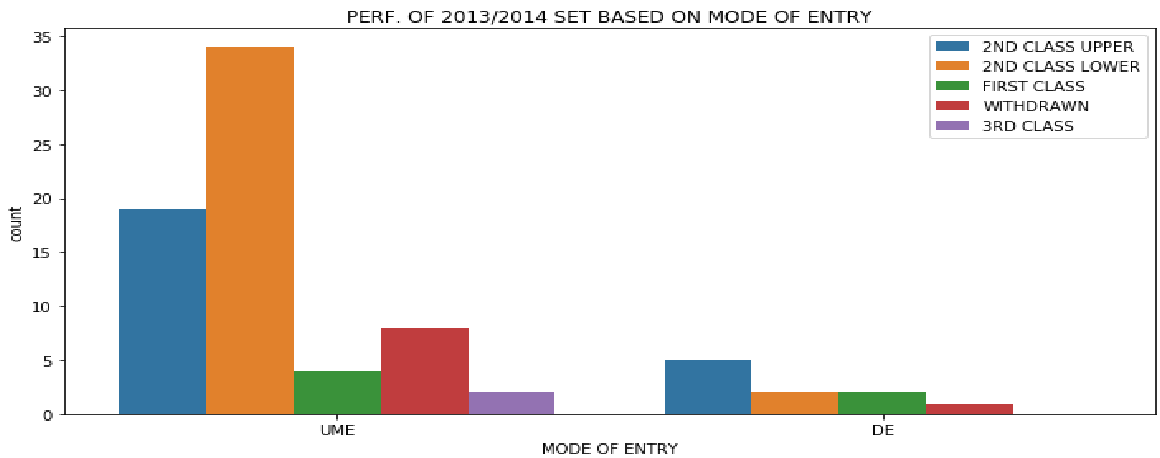

Figure 3: Performance of 2013/2014 Set Based on Mode of Entry

Figure 3 above shows that in 2013/2014 session, the students admitted through Direct Entry performed better than the UTME students.

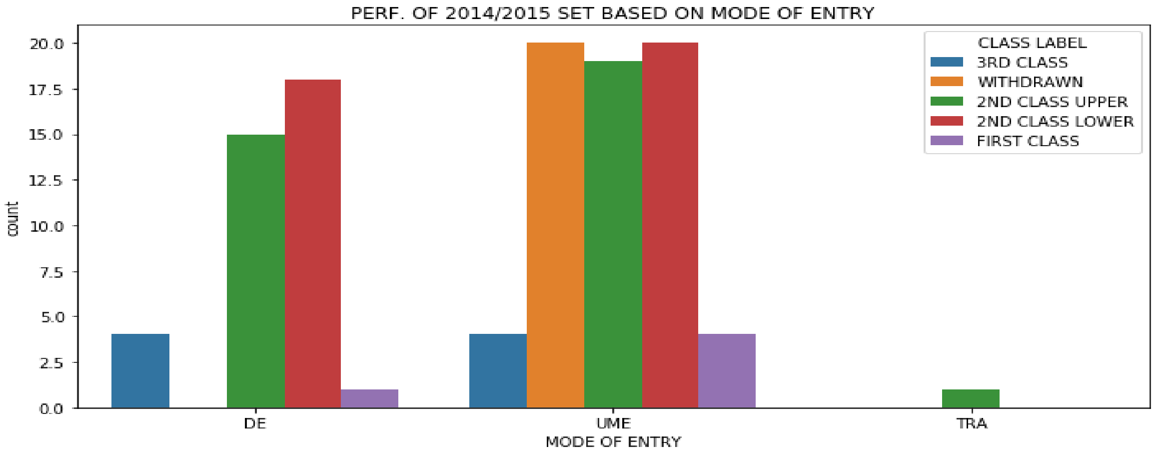

Figure 4: Performance of 2014/2015 Set Based on Mode of Entry

Figure 4 above shows that in 2014/2015 session, both have an average performance which is very close to each other.

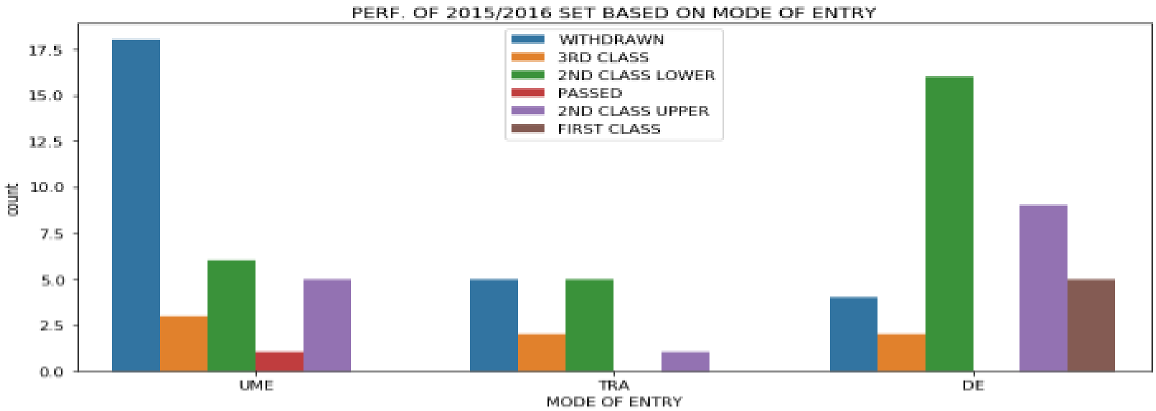

Figure 5: Performance of 2015/2016 Set Based on Mode of Entry

However, figure 5 shows that in 2015/2016 session, the Direct Entry students again out-performed the UTME students.

Figure 6: Performance of 2013/2014 Set Based on Residence

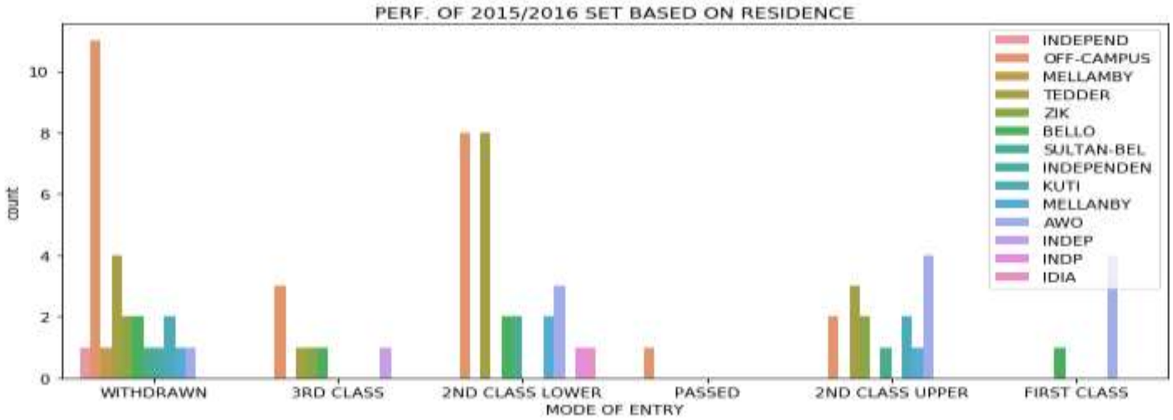

Figure 7: Performance of 2015/2016 Set Based on Residence

Figure 6 and 7 show that Students staying in the school hostel (Hall) also performed better than those staying Off-Campus.

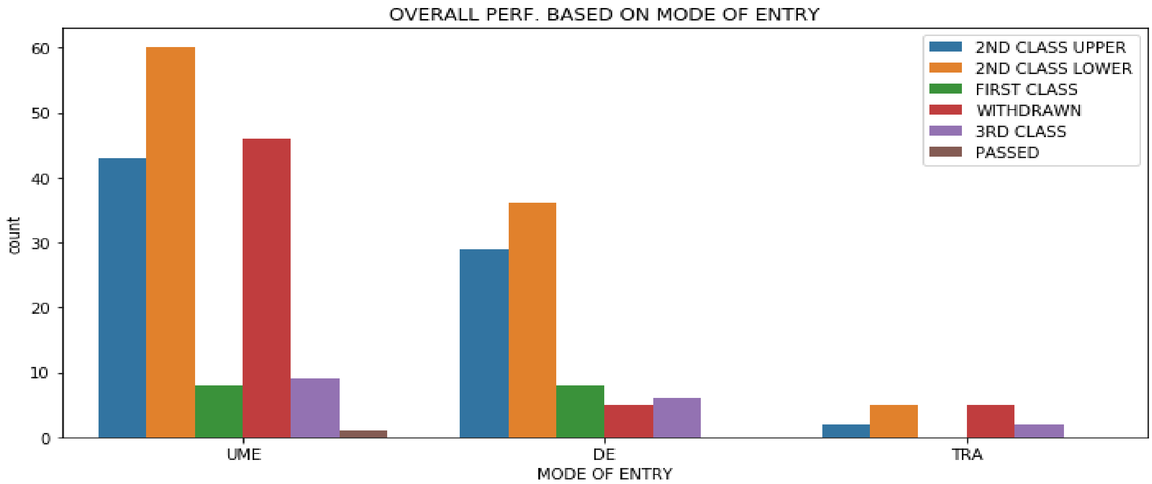

Figure 8: Overall Performance Based on Mode of Entry

In figure 8, considering the overall case, higher percentage of the UTME students are withdrawn compared to their DE counterparts. Also, a large percentage of transferred students usually do not graduate.

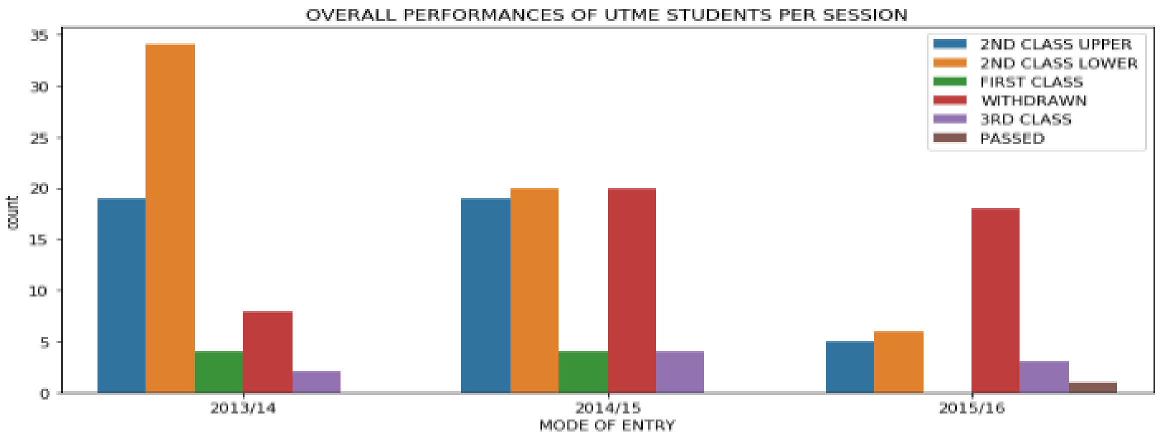

Figure 9: Performance of UTME Students Per Session.

According to Figure 9, the general performance of UTME Students had been on the decline since 2013/2014. The percentage of withdrawals were on the increase.

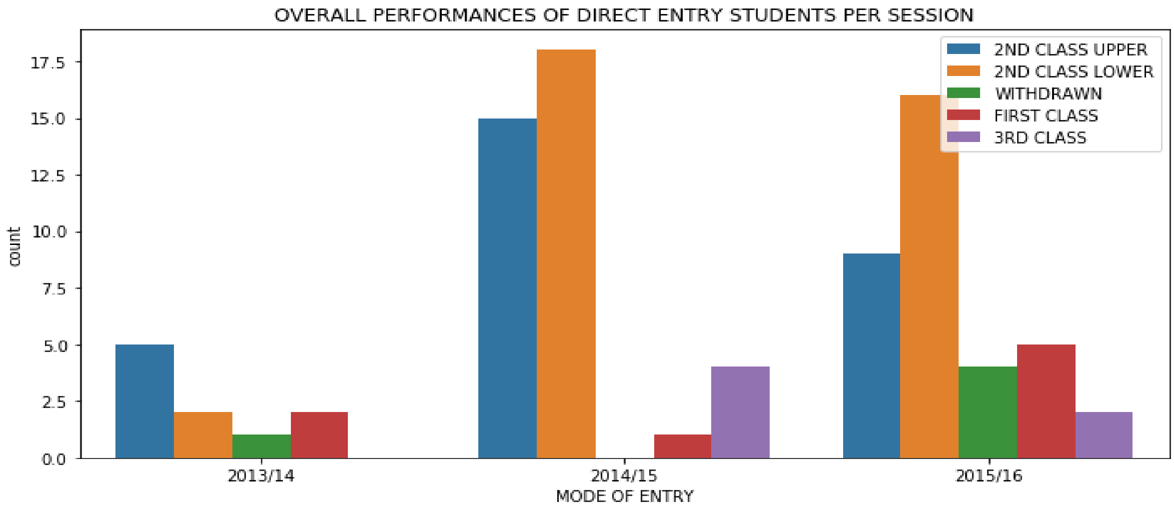

Figure 10: Performance of DIRECT ENTRY Students Per Session

While in Figure 10, DE students' overall performance had been on the increase from 2013/2014 session to 2015/2016 session.

Table 1: The actual values against the predicted values from each model

	TRUE VALUE	KNN Predicttion	SVC Prediction	Decision Tree Prediction	Random Forest Prediction	Naive Nayes Prediction
243	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS UPPER
160	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER
257	2ND CLASS LOWER	2ND CLASS UPPER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS UPPER
256	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
110	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
236	FIRST CLASS	FIRST CLASS	FIRST CLASS	FIRST CLASS	FIRST CLASS	FIRST CLASS
52	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER
263	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	3RD CLASS
97	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
245	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER
140	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS UPPER
207	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
59	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER
205	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
111	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER
234	FIRST CLASS	2ND CLASS UPPER	FIRST CLASS	FIRST CLASS	FIRST CLASS	2ND CLASS UPPER
46	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS UPPER
128	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
139	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
213	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN	WITHDRAWN
83	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER
112	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER
218	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER
208	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS LOWER	2ND CLASS UPPER
239	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER	2ND CLASS UPPER

Table 2: The model performances in terms of accuracy (%) of predictions

	MODEL	ACCURACY
0	KNN	90.6
1	SVC	96.2
2	DT	100.0
3	RND FOR	98.1
4	NB	67.9

	MODEL	ACCURACY
2	DT	100.0
1	SVC	96.2
3	RND FOR	92.5
0	KNN	90.6
4	NB	67.9

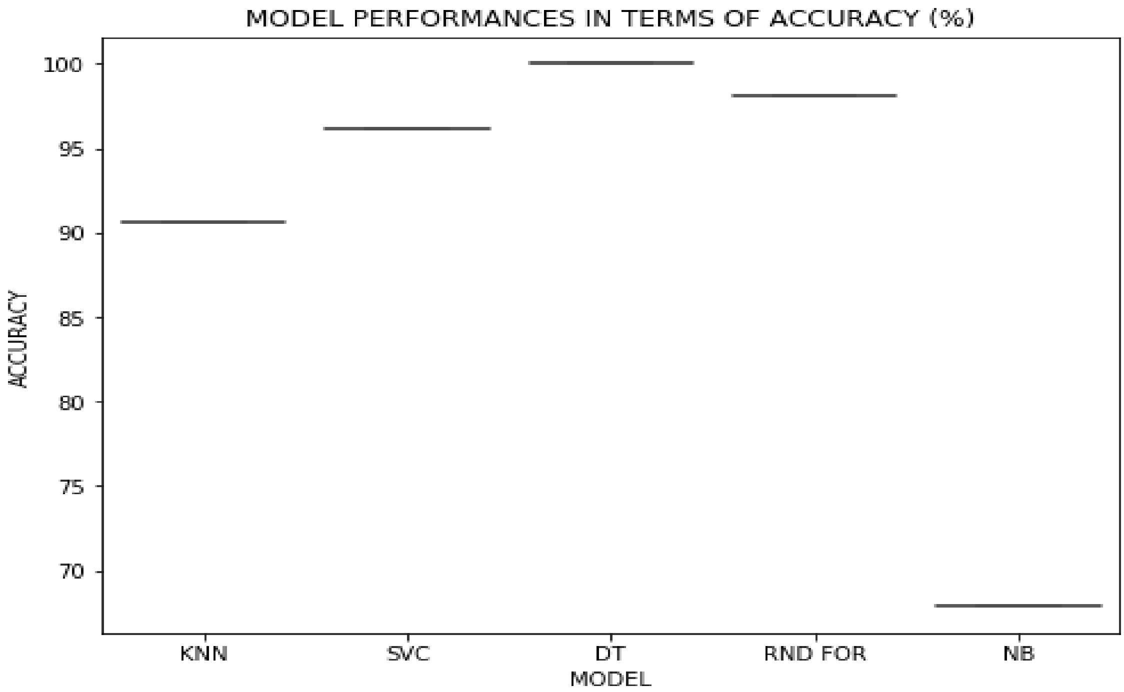

Figure 11: Boxplot of Model Performances in Terms of Accuracy (%) of Predictions

Five machine learning models were implemented to predict student academic performance. Table 1 shows some of the actual and predicted values by each model. In Figure 11, the models comparison is shown in a box plot chat. The model accuracies are plotted on the x-axis and the models are on the y-axis. Table 2 shows the performance evaluation of the models implemented in this research. The result shows that 100% prediction accuracy was gotten from Decision Tree Classifier model while K-Nearest Neighbors, Support Vector Machine, Naïve Bayes Classifier and Random Forest gave 90.6%, 96.2%, 67.9%, 98.1% respectively. The Decision Tree Classifier outperforms Random Forest largely because of the small size of the dataset, followed by SVC with 96.2% prediction accuracy and then, Random Forest Classifier, 92.5; KNN, 90.6 and Naïve Bayes Classifier, 67.9% prediction accuracy.

4.1 Model Evaluation

The implemented model were evaluated using Accuracy, Precision, F1 Score and Recall. Figure 12, 13, 14, 15 and 16 show the confusion matrix, precision, f1-score and accuracy of the Decision Tree classifier, Support vector Machine, Random forest, KNN and Naive Baiyes respectively.

```
Decision Tree
*************

[[20  0  0  0  0]
 [ 0 13  0  0  0]
 [ 0  0  4  0  0]
 [ 0  0  0  5  0]
 [ 0  0  0  0 11]]
                 precision    recall  f1-score   support

2ND CLASS LOWER       1.00      1.00      1.00        20
2ND CLASS UPPER       1.00      1.00      1.00        13
      3RD CLASS       1.00      1.00      1.00         4
    FIRST CLASS       1.00      1.00      1.00         5
      WITHDRAWN       1.00      1.00      1.00        11

    avg / total       1.00      1.00      1.00        53

Accuracy:  1.0
```

Figure 12: The confusion matrix, accuracy, precision and f1-score of the Decision Tree Model.

```
Support Vector Classifier
*************************

[[18  2  0  0  0]
 [ 0 13  0  0  0]
 [ 0  0  4  0  0]
 [ 0  0  0  5  0]
 [ 0  0  0  0 11]]
                 precision    recall  f1-score   support

2ND CLASS LOWER       1.00      0.90      0.95        20
2ND CLASS UPPER       0.87      1.00      0.93        13
      3RD CLASS       1.00      1.00      1.00         4
    FIRST CLASS       1.00      1.00      1.00         5
      WITHDRAWN       1.00      1.00      1.00        11

    avg / total       0.97      0.96      0.96        53

Accuracy:  0.9622641509433962
```

Figure 13: The confusion matrix, accuracy, precision and f1-score of the SVM Model.

```
Random Forest
*************

[[20  0  0  0  0]
 [ 0 13  0  0  0]
 [ 1  0  3  0  0]
 [ 0  1  0  4  0]
 [ 2  0  0  0  9]]
                  precision    recall  f1-score   support

2ND CLASS LOWER       0.87      1.00      0.93        20
2ND CLASS UPPER       0.93      1.00      0.96        13
      3RD CLASS       1.00      0.75      0.86         4
    FIRST CLASS       1.00      0.80      0.89         5
      WITHDRAWN       1.00      0.82      0.90        11

    avg / total       0.93      0.92      0.92        53

Accuracy:  0.9245283018867925
```

Figure 14: The confusion matrix, accuracy, precision and f1-score of the Random Forest Model.

```
K-Nearest Neighbours
********************

[[18  2  0  0  0]
 [ 0 13  0  0  0]
 [ 1  0  2  0  1]
 [ 0  1  0  4  0]
 [ 0  0  0  0 11]]
                  precision    recall  f1-score   support

2ND CLASS LOWER       0.95      0.90      0.92        20
2ND CLASS UPPER       0.81      1.00      0.90        13
      3RD CLASS       1.00      0.50      0.67         4
    FIRST CLASS       1.00      0.80      0.89         5
      WITHDRAWN       0.92      1.00      0.96        11

    avg / total       0.92      0.91      0.90        53

Accuracy:  0.9056603773584906
```

Figure 15: The confusion matrix, accuracy, precision and f1-score of the KNN Mode

```
Naive Bayes
*************

[[ 6 10  4  0  0]
 [ 0 11  0  2  0]
 [ 0  0  4  0  0]
 [ 0  1  0  4  0]
 [ 0  0  0  0 11]]
                  precision    recall  f1-score   support

2ND CLASS LOWER       1.00      0.30      0.46        20
2ND CLASS UPPER       0.50      0.85      0.63        13
      3RD CLASS       0.50      1.00      0.67         4
    FIRST CLASS       0.67      0.80      0.73         5
      WITHDRAWN       1.00      1.00      1.00        11

    avg / total       0.81      0.68      0.65        53

Accuracy:  0.6792452830188679
```

Figure 16: The confusion matrix, accuracy, precision and f1-score of the Naive Bayes Classifier.

The algorithms were evaluated using accuracy, precision, recall and f1-score. This paper shows that Decision Tree performed better in comparison to the reviewed existing machine learning methods.

This work, by inference, affirms that given certain admission related information and previous secondary school records of a prospective candidate, the system guides the admission requirements of tertiary institutions and aids its management in making efficient and effective decision as it relates to admission of students. Also, beyond admission of prospective candidates, there is provision for appropriate advisory measure to individual students in order to ensure sustenance of good academic performance.

5.0 Conclusion

The use of machine learning and data mining computational techniques for prediction in this work is a significant tool and do represent a useful model for implementing a decision support system for helping both students and student's advisors in tertiary institution to early recognize those students who are likely to exhibit poor performance. In this work, a user-friendly decision support tool is developed for predicting student's performance using a case study of Department of Computer Science, University of Ibadan. Five machine learning algorithms were implemented which include Decision Tree, Support Vector Machine, Random Forest, KNN and Naive Bayes Classifier and the result archived in respect to accuracy are 100%, 96%, 92%, 90% and 67% respectively. The Decision Tree model performed better than all other implemented models and achieved the best result in terms of accuracy. Further work to this research would apply machine learning algorithms to support individualized learning.

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