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PREDICTING PERSONNEL APPOINTMENT IN THE NIGERIAN ARMY USING PERFORMANCE RECORDS AND MACHINE LEARNING TECHNIQUES

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ABSTRACT

Professionalism and discipline in the Nigerian armed forces have been negatively impacted due to a lack of structured methods of promotion, appointment, and succession in the rank and file of military officers. This lacuna is an attribution of the socio-cultural diversities in Nigeria dispensed through nepotism, favouritism, and ethnicity. Thus, validates the need for pellucid techniques for personnel appointment at the higher echelon based on merit. This paper aims to promote professionalism in the armed forces through a model of seamless human resource processing of enthroning a seamless and transparent culture of succession based on personnel performance records. Supervised learning techniques are adopted for this research given labelled data of 10, 000 records of officers from the rank of major general eligible for appointment as the chief of army staff from the year 1990 to 2002. Relevant features were extracted from the dataset during pre-processing to filter noise, and resampled using sci-kit random over sampler to generate augmented data to balance the target class in order to eliminate algorithmic bias toward the underrepresented class. Three classification algorithms were used comparatively for modelling. The result obtained in terms of accuracy is Logistic regression 84%, decision tree 92%, and random forest 92%. The findings in this research show that our best model random forest will be 92% correct every time prediction is made with a 95 AUC score signifying 95% correctness in distinguishing between the two target classes. This research is the first of its kind and gives room for further improvement with a larger dataset.

Keywords: Appointment, Personnel, Military, Nigerian army, Performance records, classification algorithm.

1. INTRODUCTION

Over the years, the Nigerian Army (NA) has encountered several issues as a result of unstructured succession process, and computational methods used in the promotion and appointment of officers especially at the highest echelon of the armed forces. This had led to premature retirement of senior and experienced officers. To promote professionalism in the Nigerian army, it is imperative to boost the morale of serving officers through a meritorious reward system. This could be feasible through a pellucid appointment process devoid of human influence. Kakulapati et al (2020) asserted that job promotion is crucial to keep employees motivated, propelling the development of healthy and competitive skills among employees. Thus, there is a need to integrate the organization's operational data across all units and formations in the NA and provide controlled access to the data. The data could be a clever decision-making making process.

Artificial Intelligence has been employed across various domains of military operations such as surveillance, strategic and operational planning, as well as logistic support to troops in the theatre of operations. Albeit, it is yet to be fully entrenched in personnel welfare such as posting, promotion, and appointment, whereas the use of auto systems system for employee promotion has gained momentum in the civil sphere.

Kaggle in March 2021 put forward a competition to build models to predict employees' promotion (Zaman, 2021). This was a strategic effort to ensure the use of employee's performance records for promotion, this process will not only be fair but encourage good work ethics among the employees with assurance of reward based on merit. Hugo (2019) conducted similar research, though it was not predicting employee chances for promotion but the study utilized same methodology to predict the likelihood of being employed considering personal and post-employment features. Similarly, Sarker et al. (2018) apply machine learning techniques to analyse employees information for improving his/her position in the organization.

There is a growing concern among researchers in respect to the application of ML and artificial intelligence for personnel promotion in the military. In the paper "The Current Officer Evaluation and Promotion" the promotion system used by the United States Air Force, was examined by Bradley (2010). Schuller *et al.* (2021) studied how artificial intelligence might help decision-makers get more from Officers' performance records by employing supervised ML to text data as a form of natural language processing. Similarly, Nepal *et al.* (2020) leveraged machine techniques to detect the job promotion period, taking the physiological and behavioural information patterns of N=141 workers who were promoted within the period of 60 days using mobile sensing. Fallucchi *et al.* (2020) developed a decision support system that is based on objective data analysis with the goal of understanding how these factors influence employee attrition.

The goal of this paper is to use different machine learning classification algorithms comparatively to develop a model based on officers' performance records that can predict with a high level of accuracy, personnel that will be appointed the chief of army staff (COAS) with a given year or forecast future likelihood. Also, develop a model that would serve as a decision support system that would assist the governing council and the military institution in selecting and evaluating courses of action by providing a logical, usually quantitative analysis of the relevant factors (Schuster, et al. 2007).

2. MATERIALS AND METHODOLOGIES

The dataset used for this research was generated based on the conventional techniques used by the Nigerian Army and the governing council for appointing a chief of army staff (COAS). The main criteria used for appointment are shown in table 1, with priority given to Teeths Arms Corps in command appointments.

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a. Data Preprocessing
Descriptive statistics revealed there are no missing values, inconsistent data, outliers, or duplicate entries in the data set.

b. Exploratory Analysis
Exploratory analysis was done using two Python libraries Seaborn and Matplotlib to gain more insight on the data and view the relationship in among the distributed features.

c. Feature Selection
There are 17 feature features in the dataset, but only 6 features were selected for building the model. The features were selected based on domain knowledge. The features selected are the most relevant to the research as shown in table 1. Furthermore, a multicollinearity test is done to check whether any of the feature are closely related. Fig 1 shows the relation between the features.

d. Feature Resampling
Majority of the algorithm will be bias toward the underrepresented class. Fig 8 show the representation of the two instances in the target class. It shows the distribution is widely dispersed one class represented only 10% of the others. This could cause the algorithm to be skewed toward the more populated instance, a common problem with classification algorithms. To resolve this problem, sik-learn random over sampler was used to upscale the underrepresented instance. Upscaling generated more augmentations for the model as shown in Fig 9. **e. Label Encoding**

The features contain categorical data which cannot be fitted into the model, therefore it was encoded to numerical form. Since there is priority attached to the features representing performance records graded from A to E. Ordinal encoding was done on the features to represent the order from 1 to 5 in place of A to E.

f. Model
To develop the model, the dataset was split into a 70% train set and a 30% test set in which the train set was validated using a fold cross-validation. Three models Logistic Regression, Decision tree, and Random forest were implemented on the dataset.

2.1. Equations

The mathematical evaluations of the model performance is represented by the following equations.

I. $$\boldsymbol{accuracy} = \frac{(\boldsymbol{TP}+\boldsymbol{TN})}{(\boldsymbol{TP}+\boldsymbol{TN}+\boldsymbol{FP}+\boldsymbol{FN})}$$

II. $$\boldsymbol{precision} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP}+\boldsymbol{FP})}$$

III. $$\boldsymbol{recall} = \frac{\boldsymbol{TP}}{(\boldsymbol{TP}+\boldsymbol{FN})}$$

IV. $$\boldsymbol{f1} = \boldsymbol{2} * \left(\frac{\boldsymbol{recall} * \boldsymbol{precision}}{\boldsymbol{recall} + \boldsymbol{precision}}\right)$$

Where:

TP = True positive

FN = False negative

TN = True negative

FP = False positive

2.2Tables and figures:

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S.No	Features	Definition
I	**Cadet performance**	The cumulative grade point of an officer while at the defense academy. The highest grade is A and the lowest E.
II	**Appt**	Column indicating officers that were appointed chief of army staff and does that were not during the considered timeline.
III	**Discipline**	Graded point of a personnel's discipline quota.
IV	**Corp**	An organized subdivision of the military establishment
V	**PJS**	The cumulative grade point of personnel in junior officer's promotion exam.
VI	**PSC**	The cumulative grade point of personnel in senior officer's promotion exam.

Table 1: Dataset dictionary

Fig1 shows weak correlation between the independent variables in the dataset signifying no multicollinearity.

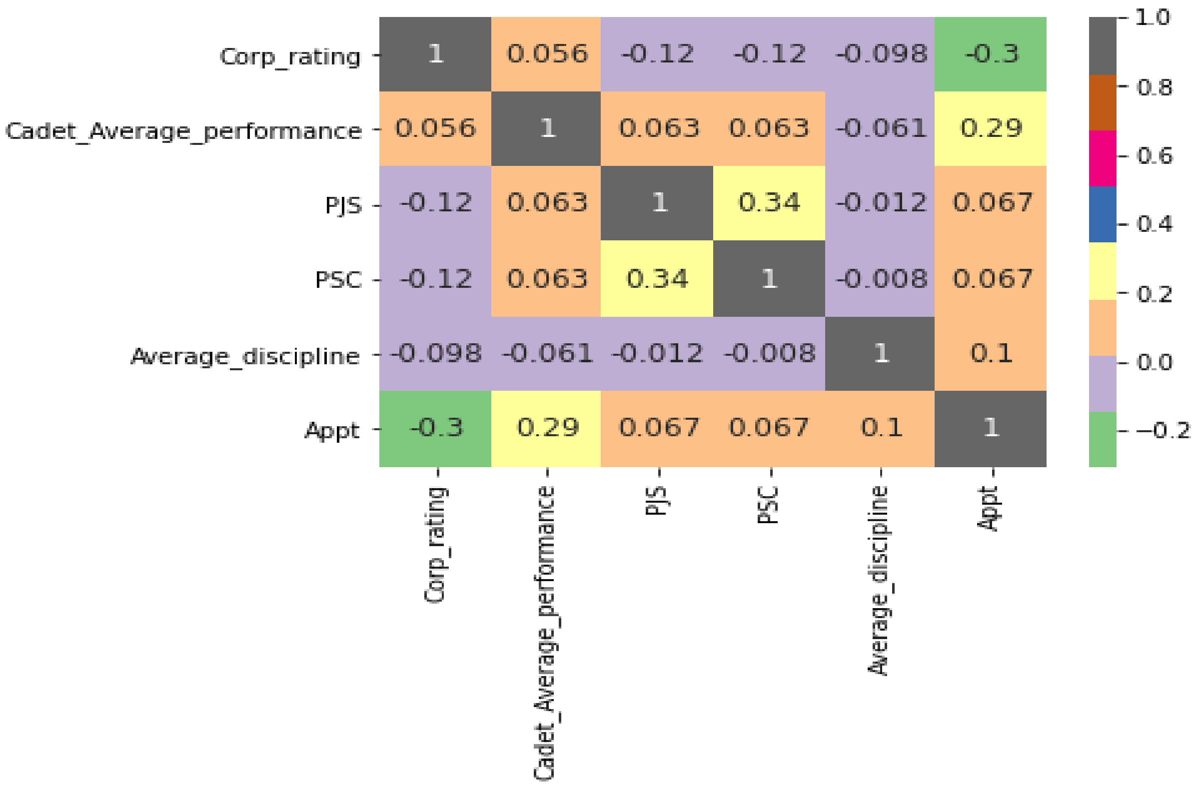

Fig 1. Heatmap showing the relationship between Features

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Fig 2. Logistic Regression model confusion matrix

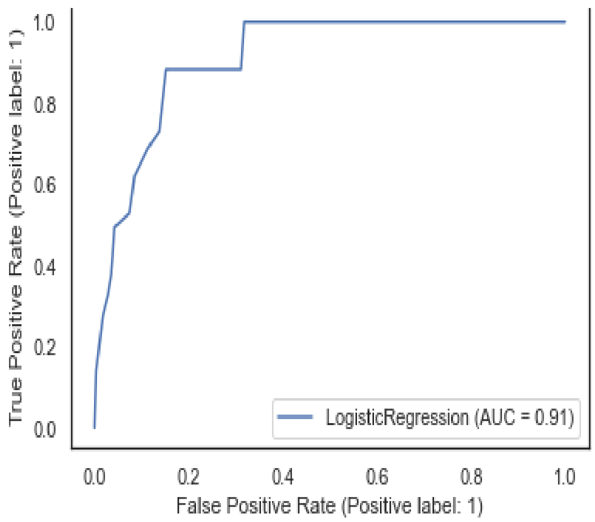

Fig 3. Logistic Regression AUC curve

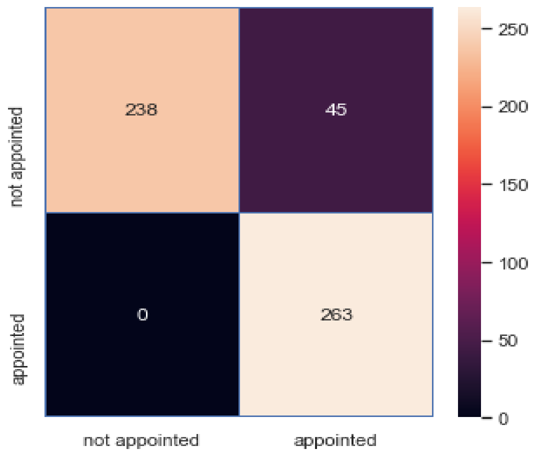

Fig 4. Decision Tree confusion matrix.

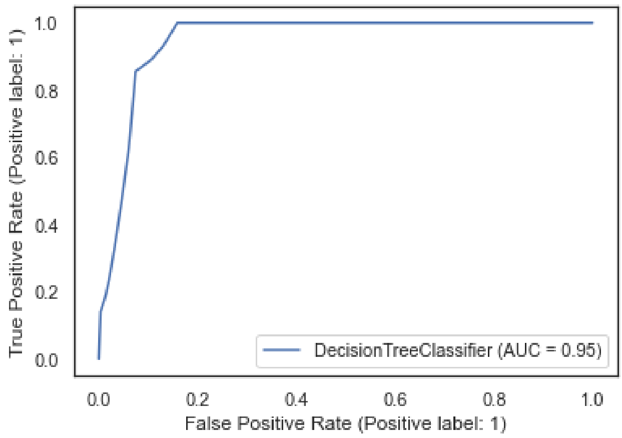

Fig 5. Decision Tree AUC curve

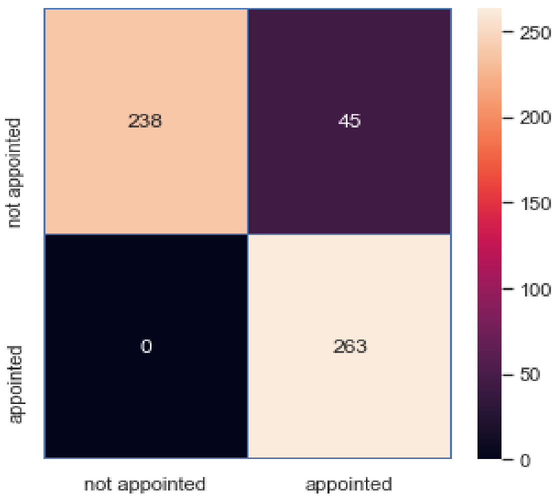

Fig 6. Random Forest confusion Matrix

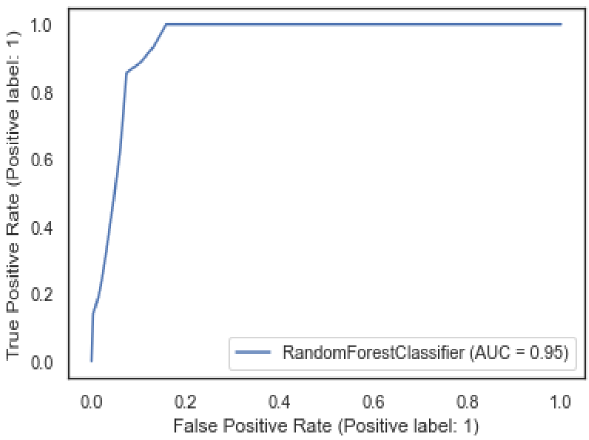

Fig 7. Random Forest AUC curve

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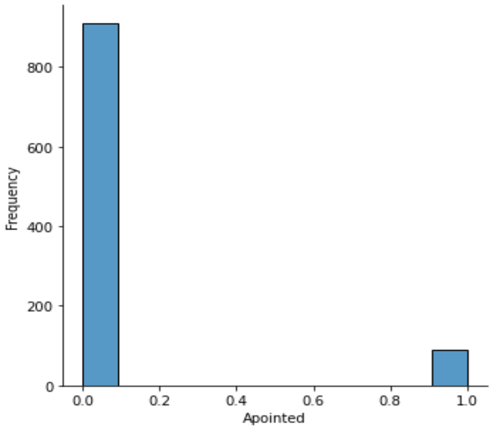

Fig 9 Distribution of resampled data in the target class

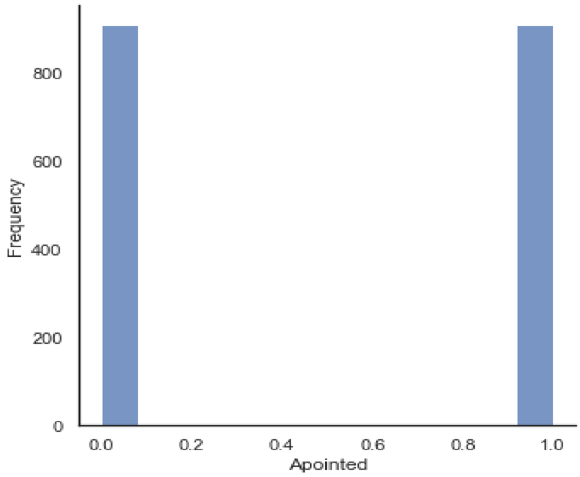

Fig 8. Distribution of data in the target class

Table II: Comparative Model Performance

S/N	Classifier	Accuracy	Precision		Recall		F1 score		AUC score
			0	**1**	**0**	**1**	**0**	**1**	
I	Logistic regresion	0.84	0.88	0.80	0.80	0.88	0.83	0.84	0.91
III	Decision Tree	0.92	1.00	0.85	0.84	1.00	0.91	0.92	0.94
III	Random Forest	0.92	1.00	0.85	0.84	1.00	0.91	0.92	0.95

3. RESULTS & DISCUSSION

The performance of the three models as shown in Table 2 is very encouraging, with the presented figures we are over 80% confident that our models will make accurate predictions. To establish a solid understanding of our findings, each model will be analyzed using equations, figures, and tables presented in the methodology.

Three classification algorithms from the sci-kit-learn python library were applied directly to the dataset. However, the model developed with the Decision Tree (DT) and Random Forest (RF) algorithm produced same results across all metrics, with an accuracy of 92%, an average precision of 92.50%, recall of 92%, f1 score of 91.50% for both instances 0 and 1, and AUC score of 94% and 95% respectively. Logistic regression (LR) accuracy is 84%, an average precision of 84%, recall of 84%, f1 score of 83.50% for both instances 0 and 1, and AUC score of 91%. Decision Tree and Random Forest model were the most efficient going by the evaluation metrics in contrast to the Logistic Regression. Although DT and RF model seems to perform relatively the same, the ±1 difference in the AUC score as shown

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in the comparative model performance in Table 2 signifies RF as our best mode.

Logistic Regression: With the figures presented based on the evaluation metrics in Table 2, the logistic regression model will be 84% accurate in making generalizations. That is, it will be 84% correct whenever it predicts appointed or not appointed (0 or 1). However, the accuracy doesn't say much about how the model is predicting each instance (0 or 1) in the target class. Mathematically accuracy is represented by Eq1. However, precision and recall present more information on how the model is making predictions. Table 2 shows that the logistic regression has more precision in classifying the 0s than the 1s, this is explained by the confusion matrix in fig2 where the model classified 58 features labeled appointed (1) as not appointed (0).

Precision is represented by Fig 2. The model's high recall for 1s resulted in fewer classifications of not

Appointed (0) features as appointed (1) as shown in Fig 2. The total features labeled as not appointed but classified as appointed were only 31. Eq3 is the mathematical the model is efficient and the methodology concise, but it is imperative to address some underlying concerns that might bother a reader of this paper to grasp how the model is intended to be deployed. The question that only one senior officer can be appointed COAS in a considered period might arise, however, if the model predicts a tie hierarchy will be considered. The Nigerian army is an institution rooted in discipline and professionalism, therefore hierarchy is of the essence. In appointing COAS priority is given to the Teeths Arms Corps (combat Corps) in command appointments. When there is a tie, considerations will be made based on Corp precedence. Furthermore, if officers emerge from the same Corp, the service number will be considered in ascending order whoever comes first will be appointed. The relevance of the question above is to clear any form of ambiguity and further project how our model could be employed in the appointment process. With the aforementioned, it is established that our model would not replace the existing norm but rather serve as a decision support system that will aid transparency in the system. expression of recall. The f1 score represented by Eq4 is the harmonic mean of precision and recall. AUC score is used to ascertain how the model distinguishes between the two instances 0 and 1 presented in fig3 with a line graph. 91 AUC score shows the model distinguishes the instances well.

Decision Tree and Random Forest: Both models have an accuracy of 92% signifying better prediction. The precision for both model for not appointed (0) is 100% and for appointed (1) is 85%. These models will accurately classify all not appointed instances, and as well classify the appointed up to 85% accurately and miss out on few. On the other hand, the model will recall 100% of the features labeled appointed and classify it as appointed. For clarity fig4 and fig6 shows the confusion matrix of the two models. It is seen that the matrix has 0 FP (not appointed but classified as appointed) entry, this is due to the 100% recall. Whereas there are 45 entries as TN due to 84% precision. Both models have AUC scores of 94% and 95% respectively, signifying better classification of the instances.

From the paragraph above, it can be deduced that random forest is our best model as compared to the logistic regression and decision tree, without considering the AUC score the decision tree and random forest will be on the same scale, and either could be deployed. The metric of interest in this research is precision and recall. Going by the result, we are okay with the precision / recall tradeoff. The higher recall value gives us the leverage to classify all officers who are likely eligible for the appointment, for further considerations in the appointment process. This is in line with the concerns stated earlier for implementing a seamless

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and transparent appointment process in the Nigerian army.

The outcome of this research justified Schulker *et al*. (2021) study on how machines can be used to gain insights into officers' performance in crucial decision-making. With the performance of the model, it projects an effective decision-making system. All features in Table 1 are collated through the examination process, except for the Corp which is given precedence. However, to improve the grading of the personal discipline rate Nepal *et al.* (2020) approach of using mobile sensing could be considered. Our research serves as a bedrock for the implementation of machine learning for predicting promotion, employment, and posting in the NA in the absence of related literature.

4. CONCLUSION

The absence of transparent appointment processing in the NA has led to the premature retirement of experienced senior officers. To mitigate this problem, there is a need to develop a system devoid of human influence. This can be achieved through the use of personnel performance records and machine learning to predict appointments at the higher echelon. In this paper, several machine learning techniques were used to build a model to predict eligibility for appointments as the COAS, given the historical data of appointments and officers' performance records. Several approaches related to data cleaning and model validation were discussed. The results obtained from all metrics are impressive and support the use of machine learning as a critical tool in the decision-making process in appointing officers in the NA.

Our research utilized a relatively small amount of data, due to difficulty in accessing restricted military information. Interested researchers can implement our methods with a larger dataset. The approach can be extended to predict other portfolios in the NA, Nigerian Airforce, Nigerian Navy, police force, and para-military.

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