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KNN and SVM Machine learning to Predict Staff Due for Promotions and Training

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ABSTRACT

The hope of every organization to achieve its set goal depends mainly on its human resources. Promotions and training exercise can help retain staff perceived to leave an organization which can help improve employee performance and guarantee job satisfaction. Any Organization or firms were Employees are denied of promotions and training opportunities may experience poor workplace moral behaviour among staff members. It can fuel mistakes or errors and bring about job dissatisfaction and the organization may not perform well as required, leading to even lower retention and turnover rate. The lack of promotions and training exercise directly affects the general performance; it can lead to financial loss and exit of experience employees from the organization. The KNN and SVM model was developed, trained, tested and evaluated using the same dataset with the help of grid search cross validation test. The grid search technique was employed to select the best and optimal kernel and support vector value in predicting those due for promotions and training. The experimental results of KNN produced 78% and SVM that gave 91% success rate as the best.

Keyword: *Machine learning, K-nearest neighbor, support vector machine, promotions, Training*

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I. INTRODUCTION

The Employee job training and promotions exercise on work motivation are very vital and important in every organization to have a better and reliable system. This requires a better human resource(HR) management system that takes into consideration employee promotions and training exercise[1]. Ghaffari *et al.*,[2] stated that promotions and training has a positive impact on employee performance that every organization should take into consideration. Organizations should take note that promotions and training are very vital and changes occur continuously in different situations, needs and individual goals may arise and managers should note that different incentive attached to promotions and training can positively affect employee moral behaviour in different ways, position and time. A research carried out by Khan *et al.*[3] that organizations or firms that have adequate and excellent training and promotion plan for its employees will improve job performance among its members and guarantee members job satisfaction. Lack of promotion and training exercise may lead to low performance and retention rate as one of the most obvious outcome which results into less output, more errors, and quality issues, time repeating activities, no job satisfaction and low moral behaviour among staff members. Promotions and training exercise help retain staff perceived tendency of leaving the organization with or without a prior knowledge which can positive affect employee performance and job motivation. The aim is to build K-nearest neighbor(KNN) and support vector machine(SVM) learning model capable of predicting Staff due for promotions and training in avoiding the sudden exit of highly experienced staff in every organization.

This paper is divided into different sections as followings: section 1 contained the introduction, section 2 presents a brief review of previous approaches relating to the study area and the gap in exploring the proposed model; Section 3, introduces materials and methods employed for developing the model; Section 4, focuses on the results and detailed discussion of results; Section 5 presents the conclusion to the paper.

II. RELATED WORKS

There are several factors that causes poor employee moral behaviour among Staff; namely: The Organizational factors[4]. The organizational factors includes: low salary, training, too many requirements for promotions and lack of appreciation for job well done etc[5]. There are other factors identified by Morrell[6] as new rules and organizational policies, not been involved for staff training employees, lack of monetary benefits to training and promotion exercise. The skilled and highly experience employees are considered asset to any organization; therefore, a good and flexible working environment is recommended to retain the above factors[7]. Balcioglu[8] employed KNN as a non-parametric machine learning algorithm capable of estimating the employee turnover scenario. The KNN technique was developed, trained, tested and validated to predict the employee turnover probabilities across different kernel(k) values using a dataset generated through IBM Watson software. The performance accuracy of KNN in terms of precision across different k values ranges from 1, 4, 6 to 8 which produced 95%, 92%, 93% and 90% accuracy rates. The results show that losing experience staff within the organization is likely to waste investment in employees. The KNN resulted in misclassification error caused by model over-fitting and required other data sampling techniques to produce a better and reliable system. Abugre and Anlesinya[9] carried out a cross-sectional survey and discussed the influence of training participation on employee and perceived employee tendency of leaving manufacturing firms as a result of not been featured in training exercise. The attributes of employee experience, work hour and skill features are used to qualify employees for training exercise. The results show that the organizational tenure, experience, work hour and skill feature has a significant and positive impact on employee performance and participation in an organization. The model could not be developed, trained and tested to work well with real life data. Nawaz *et al.*,[10] proposed a workable framework to show the impact of training and empowerment on employee creativity using a field survey made up of 400 items obtained from 110 organizations comprises of textile, FMCG, cement, petroleum, fertilizers, pesticides, chemicals, electronics, pharmaceuticals and etc. The results reveals that employee partial training participation mediates against the relationship between human resource(HR) practices and staff creativity. The research was carried out to work best with sizable dataset. Ogbuabor and Malaolu[11]; carried out an empirical study on the effect of employee training, manpower development on the overall organizational performance. The study adopted some theoretical machine learning techniques for visualization and used First Bank of Nigeria as a case study. The results shows that greater percentage of the respondents about 70% states that training and manpower development enhanced their efficiency with employee job productivity and the general organizational performance. Recommends that employee training programs should be made compulsory for every individual to motivate and improve performance so that other staff in turn can aspire to perform well and excel. The accuracy rate of adopted techniques could not be computed to work with real life data as such required the use of other machine learning techniques that can work well with practical implementation like the proposed system. Ogbodoakum *et al.*,[12] examined the role of peer and superior support, training self efficacy and training needs using a descriptive survey of statistical techniques that uses machine learning like methods in their predictions like the ARIMA's model for employee readiness to participate in training exercise. The model accuracy rate was below average cause by over-fitting and misclassification errors, resulted in biasness and required improvement using other machine learning techniques. Long *et al.*,[13] combined the random forest and KNN data mining techniques to predict employees that are due for promotion using basic and post features based on some strategies. A preliminary correlation analysis was conducted to explore the associations between selected features and promotion. The post features had higher impact on employee promotion compared to personal basic features. The Gini importance value was computed for each future on employee promotion. The random forest performed best and verified the validity of the selected features compared to the KNN mining technique. Elnaga and Imran [14] proposed a theoretical frame work to determine the impact of training on employee performance and suggest ways on how to improve employee performance through training exercise. The study revealed about training effectiveness and how it contributes meaningfully to increase employee performance. The model could not be used to overcome deficiencies in employee performance and training on job. The results shows that training has positive impact on employee performance. Punnoose and Ajit [15] Constructed an employee turnover prediction system using extreme gradient boost(XGBoost), logistic regression, Naive Bayes, RF, SVM and KNN machine learning classifiers. The GBoost produced 88% as the best accuracy compared to others. It required a well-structured and sufficient hidden layer approach to improve the accuracy and scalability of predicting employee turnover.

III. MATERIALS AND METHODS

In this paper, **we** focused on the use of KNN and SVM machine learning techniques using Grid search technique with a cross validation test to effectively overcome the problem of over-fitting with better accuracy rate and efficiently handle overlapping classifications. The Kernel and different support vector machine values are used to search for the best threshold values and achieve better performance rate. We are adopting the grid search technique with a cross validation test because by default it is sensitive to overcome over-fitting and misclassification errors.

3.1 Data source: The dataset used was obtained from a well-structured self study questionnaire distributed and collected through survey as a primary source containing one hundred and fourteen(514) items with attributes: gender, changed_jobs, exiting_jobs, involvedIn_training, promoted, job satisfaction and target. The dataset was divided into 80% training ($\frac{80}{100}\% \times 514$) = 412 items) and 20%

testing($\frac{20}{100}\% \times 514$) =102 set for predicting the perceived employee tendency of leaving an organization.

Table 1: Predicted solutions for staff due for promotions and training

	Gender	ChangedJobs	ExitingJob	Training	Promoted	Target
1	Female	Yes	Yes	No	Yes	Training
2	Male	No	No	Yes	Yes	=
3	Female	No	No	No	Yes	Training
4	Female	No	No	No	No	Train & Promote
5	Female	No	No	No	Yes	Training
6	Female	Yes	Yes	No	Yes	Training
7	Male	Yes	Yes	No	Yes	Training
8	Female	Yes	Yes	Yes	Yes	=
9	Male	Yes	Yes	No	Yes	Training
10	Male	Yes	Yes	Yes	Yes	=
11	Male	No	No	No	Yes	Training
12	Male	Yes	Yes	No	Yes	Training
13	Male	Yes	Yes	No	Yes	Training
14	Female	No	No	Yes	Yes	=
15	Female	No	No	No	No	Train & Promote
16	Male	No	No	No	No	Train & Promote
----	----	-----	------	------	------	------
489	Female	No	No	No	No	Train & Promote
490	Female	Yes	Yes	No	Yes	Training
491	Male	Yes	Yes	No	Yes	Training
492	Male	Yes	Yes	Yes	No	Promotion
493	Female	No	No	No	Yes	Training
494	Male	Yes	Yes	No	Yes	Training
495	Male	Yes	Yes	No	Yes	Training
496	Female	Yes	Yes	No	No	Train & Promote
497	Male	Yes	Yes	No	No	Train & Promote
498	Female	Yes	Yes	No	No	Train & Promote
499	Female	Yes	Yes	No	No	Train & Promote
510	Female	No	No	No	Yes	Training
511	Female	No	No	Yes	No	Promotion
512	Female	Yes	Yes	No	Yes	Training
513	Female	No	No	No	Yes	Training
514	Female	No	No	No	Yes	Training

3.2 The study strategy:

The study strategy is divided into stages which includes: preprocessing, classification, feature extraction, the model(KNN and SVM) and performance evaluation stages in a top-down approach.

3.2.1 Data preprocessing: The pre-processing stage is necessary for the training and reduces threshold value. It was adopted to help manipulate data and improve model performance because in gathering data sometimes poses difficulties and may result into out-of-range, missing, noisy and false data values. This involves data cleaning, instance selection, data normalization, transformation, feature extraction and selection. The preprocessing produces training data as output which can effectively be interpreted by models.

3.2.2 Classification: The classification system is adopted as a supervised learning process of determining data classes referred to as target, labels or categories. Classification is a predictive task or modeling of estimating a mapping function from input variables represented as "X" variable to a discrete output variable represented with "y". It depend mainly on the area of application and the nature of available dataset[16].

3.2.3 Feature Extraction: The feature selection process was adopted to determine the correlation between variable or attribute pars based on the level of correlation using a score value. The higher the score value the higher the correlation between attribute pairs[17].

3.2.4 K-nearest Neighbor: The KNN requires no assumptions about data distribution in predicting target variables[18]. It works based on observations about data features that are similar to the points in one particular class known as nearest neighbors[19]. The k parameter specifies the number of neighboring points used to classify similar data points into one class by the concept of voting[20].

We created KNN classifier object and passed the k-neighbors argument value to a function in the K-neighbors Class. The model was fitted and trained with training set using the model.fit command and predicted with model.predict command employed in Python sklearn library to perform prediction using the test dataset.

3.2.5 Support Vector Machines (SVM) regression class: The SVM is one of the simplest and more preferred machine learning techniques used by data professionals because it tendency of producing better and high accuracy with less computational error[21]. The SVM uses two main concepts namely; hypothesis space and the loss functioning finding an "optimal" hyper-plane as a solution to any learning problem[22]. The SVM is memory efficient and uses subsets of training data points in the support vectors called decision function. The simplest formulation of SVM is the linear one, where the hyper-plane lies on the space of the input data[23]. The SVM estimator was defined on the training dataset and tested to effectively predict the target variable. A SVM classifier was invoked from the sklearn.svm library in python and SVM model created. The gamma variable set to be scalable, c=1,0 and random states set to 101 with the Python script: svc=SVC(gamma='scale', C=1.0, rando_state=101). The model was trained with training dataset with svm.fit(X_train,y_test) and predicted using the testing dataset[svc.predict(X_test)]. The visualization was done using mat_plot_lib library in python. A SVM linear regression class was created with the pre-processed training data to learn and make predictions about employees training and promotions.

Algorithm 1: K-nearest neighbors(KNN)

Step	**Processes involved**
1	Start
2	Gather the unsorted dataset with known categories
3	Carryout clustering on sample data points
4	Sort data points and select the first as training samples
5	Find The K value by taking K= sqrt(n), where n = No. of samples in the dataset
6	Locate K-NN values
7	Categorize new points using the concept of majority vote
8	Return

Algorithm 2: Support vector machine(SVM)

Step	**Processes involved**
1	Start
2	Find candidate_SV with closest pair from classification (SV=>support vector)
3	If there are violating points:
4	Find violating_points
5	Compute the candidate_SV= candidate_SV + voilating_points)
6	If there is any α_p< 0 due to the addition of c to S that gives negative:
7	Candidate_SV = candidate_SV
8	Repeat module to prune all data points
9	end_if
10	end_if

3.2.6 The Grid search Method: We are using the gridsearchCV method with a cross validation test to search for the best possible threshold hyper-parameter values. The KNN and SVM nodes are trained to use feature to increase the performance and make a more stable and accurate predictions. The sklearn class library with Randomized Search CV method was adopted and defined on grid of hyper-parameter values and samples from the grid performing K-fold cross validation(CV) with combination of values. The random Grid Search was used to obtain the best hyper-parameter values with more cross validation folds in reducing the chances of model over-fitting.

3.2.7 Performance Evaluation

The prediction accuracy, mean score and standard deviation and cross validations curve are employed to evaluate the performance of KNN and SVM classes.

The accuracy is the ratio of correctly classified data points to the total no. of points in the dataset which ranges from 0-100%.

$$\text{Accuracy} = \frac{\text{Number of correct classifications}}{\text{Total number of classifications}} = \frac{TP+TN}{TP+TN+FP+FN} \qquad 1$$

Standard deviation: is the measure of variation or dispersion for set of numerical values it basically computes the square root for the spread of 'x' distribution of data from the average point. It's a computation showing how far data haves from the average or mean point

$$\text{Standard deviation (S.D)}=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{X})^2} \qquad 2$$

Where N is the total dataset, x_i is the individual observations in the sample dataset and $\bar{X}$ is the mean of the sample. We computed the standard deviation of data using the sqrt-function from math module of Python standard library with the stdev-function that takes data from a population and returns its standard deviation.

IV. RESULTS AND DISCUSSION

The results of KNN and SVM regression classes are obtained through the use of tables and Charts. The design and implementation was done with some varying fine-tuned kernel, epsilon and support vector hyper-parameter values to have a better result. The prediction and classification accuracy of both models are visualized and discussed using cross validation curve, neighborhood graph, standard deviation and mean scores reported as given bellow.

RESULTS

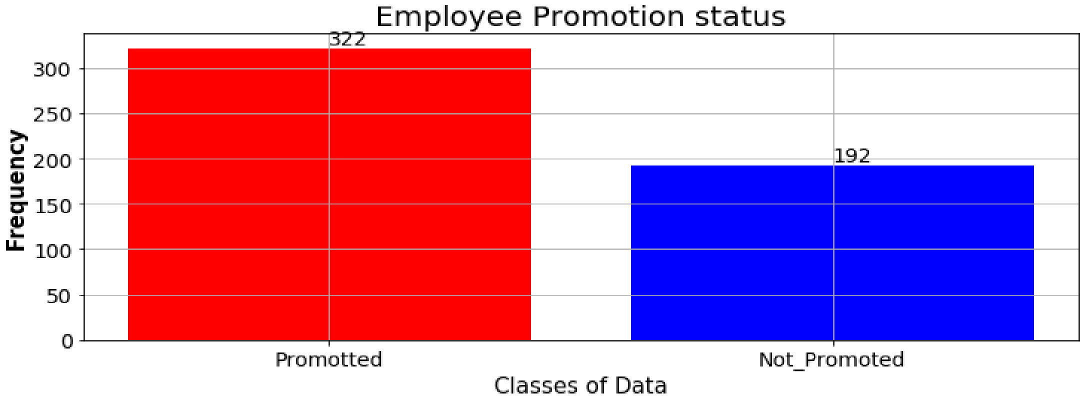

Figure 1: Employee Status of promotion

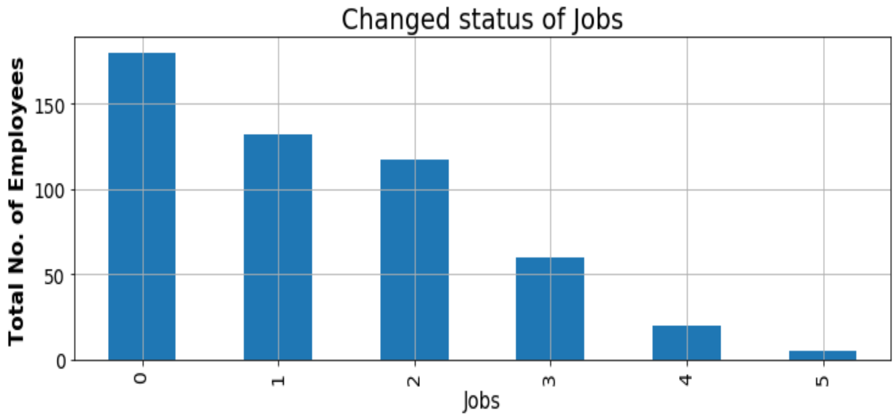

Figure 2: Changed Status of jobs

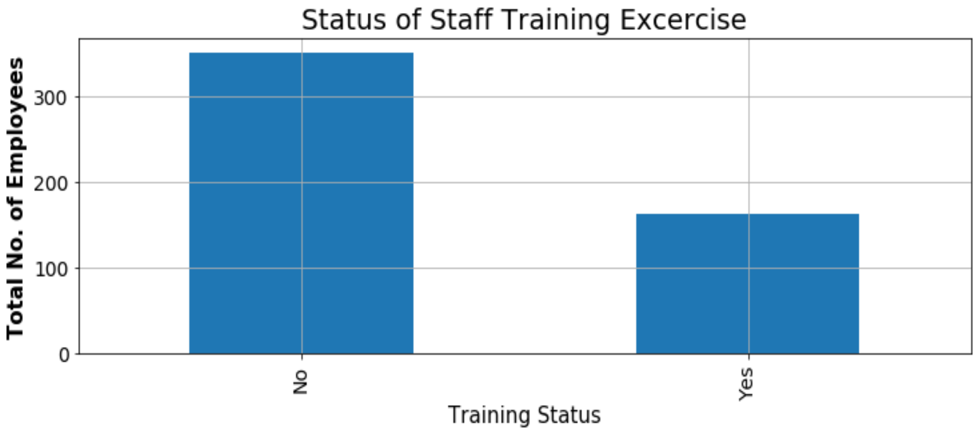

Figure 3: Status of Employee training

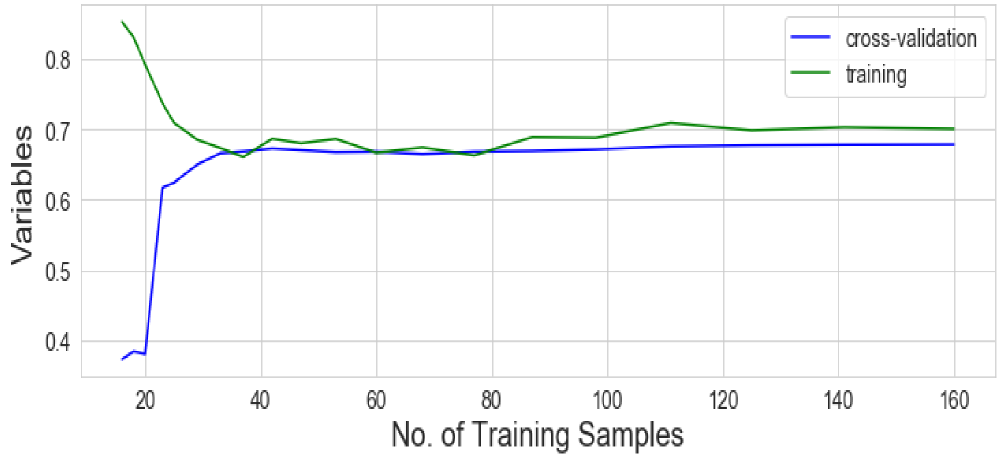

Figure 4: The SVM learning curve

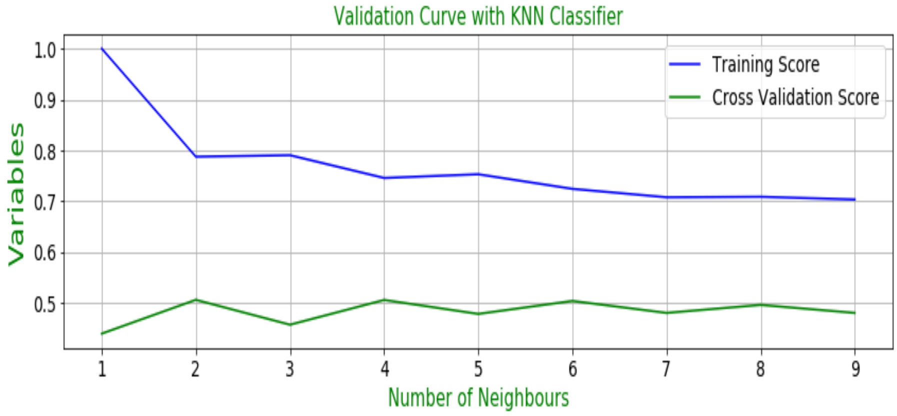

Figure 5: The learning curve of KNN classifier

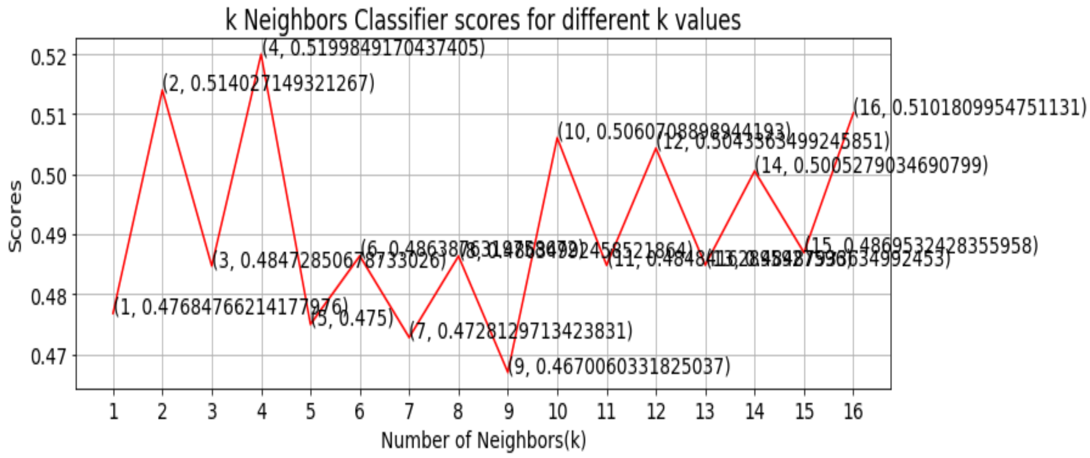

Figure 6: K-NN scores for different K-values

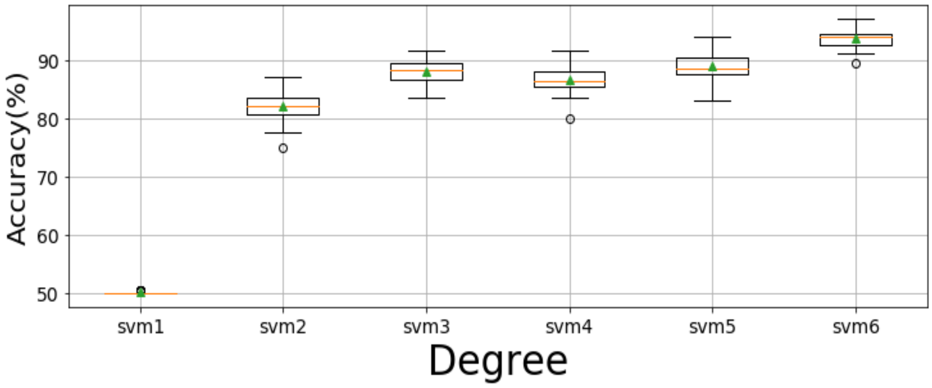

Figure 7: The support vectors

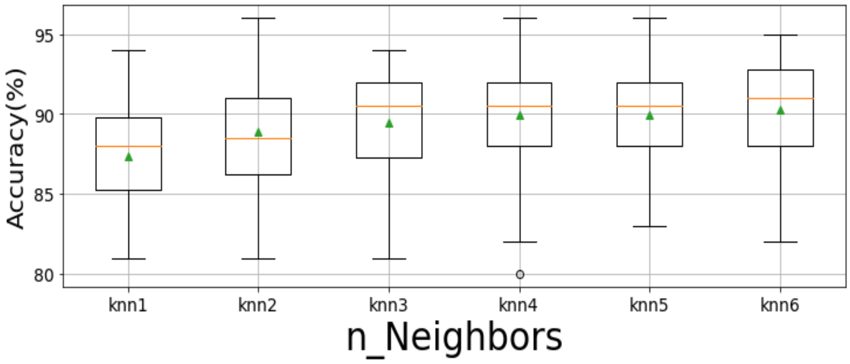

Figure 8: Status of Employee promotion

Table 3: The SVM mean score and standard deviation

SVM	Mean score	Standard deviation
1	0.501	0.002
2	0.820	0.026
3	0.889	0.022
4	0.865	0.023
5	0.889	0.025
6	0.937	0.017

Table 4: The KNN mean score and standard deviation across

K-value	Mean score	Standard deviation
1	0.873	0.030
2	0.889	0.038
3	0.895	0.03
4	0.899	0.035
5	0.900	0.033
6	0.902	0.034

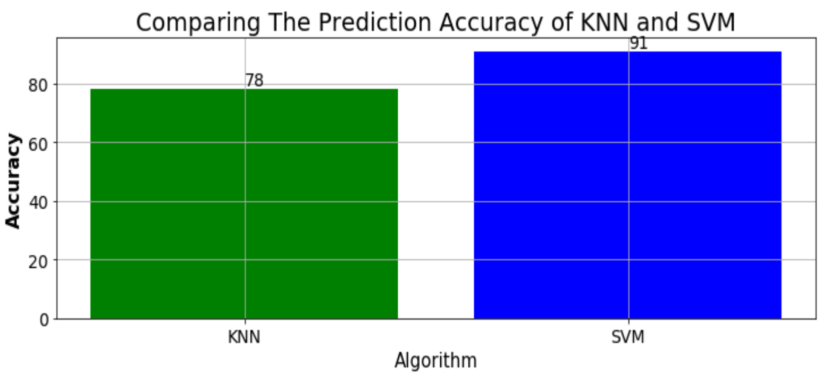

Figure 9: The metrics of accuracy

DISCUSSION OF RESULTS

Figure 1 is the chart representing classes of promoted and not promoted set of employees. The number of employees promoted and not promoted as data classes produced 322 and 192 persons represented with red and blue colors respectively

Figure 2 depicts the employee changed status of job experience as visualized and arranged in ascending order. The changed status of jobs ranges from 0, 1, 2 to 5 as obtained from the proposed system dataset for decision making purpose. The employees with 0-changed status produced the highest followed by those with status of changed jobs to be 1, 2, 3, 4 and compared to those whose job status has been changed five times as the least shown in the Bar chart.

Figure 3 is the graph showing the total number of employees trained and not featured in training exercise obtained from the dataset. The total number of Staff involved in training exercise represented with "Yes" is recorded to be higher than those not trained represented using "No" as visualized through the dataset obtained from the field survey.

Figure 4 depicts the learning curve graph of SVM. The cross validation score of SVM increases and training score decreases along different training data samples. The training and validation curve converges from point 30 across other points as shown in the learning curve.

Figure 5 depicts the graph of KNN validation curve. The cross validation score increases gradually and training score decreases generally with growing number of k-neighborhood value. The training score is higher and will continue to decrease across different k-neighbors than the validation score that increases gradually along different k-values as we increase the k-value.

Figure 6 depicts the performance of KNN for different neighbor values ranging from 0 to 30. When k-neighbors is set to 1 produced 0.47 validation score, k=2 gave .0514, k=3 produced 0.484 and k=4 with 0.514, k=5 with 0.395 and so on with cross validation score for 30 iterations. The validation score gradually increases as we increase the number of k-neighborhood values as shown in the figure above.

Figure 7 is the plot of SVM accuracy rate against the different fine-tuned support vector hyper-parameter values. The prediction accuracy increases across different values with growing number of support vector that ranges from 1, 2, 3, 4, 5 to 6 as shown in figure 6 above. The value mapped to SVM6 produced the highest prediction accuracy, followed by svm5, svm4, and svm1 gave the least accuracy rate. The prediction accuracy increases along different fine-tune hyper-parameter values of support vector as we increase the value.

Figure 8 depicts the KNN accuracy rate across different neighborhood values ranging from 1, 2, 3, to 6 obtained from the dataset. There is a significant increase of prediction accuracy against the k-neighbor value as we increase the n_Neighbors of the KNN technique. The k=6 produced 91% as the highest, followed by k=5, k=4 to k=1 having the least prediction accuracy.

Table 3 shows the mean and standard deviation scores of SVM along different kernel values ranging from 1, 2, 3, to 6. The mean ranges from 0.501, 0.820 to 0.937 and standard scores 0.002, 0.026 to 0.017 increases and gets closer to 1 as we increases the number of support vectors.

Table 3 shows the KNN mean and standard deviation scores ranging from 1, 2, 3, to 6. The mean ranges from 0.873, 0.889 to 0.902 and standard scores 0.030, 0.038 to 0034 increases and gets closer to 1 gradually as we increases the number of support

Figure 9 is a simple bar chart showing the overall prediction accuracy of KNN and SVM techniques with testing dataset. The result of SVM technique is recorded 91% higher compared to the KNN techniques that produced 79.0% prediction accuracy in carrying out training and promotion exercise.

V. CONCLUSION

The prediction of accuracy of SVM was higher and better than KNN in terms of prediction accuracy, cross validation test, mean score and standard deviation score in predicting employee promotions and training. This will help organizations predict staff due for promotions and training exercise may affect work output and serve as a benchmark to other researchers because the model is scalable. The prediction accuracy of SVM produced a maximum of 91% as the best performance level with varying fine-tuned hyper-parameter values from the results compared to the KNN with 79% accuracy rate. The use of Python programming language simplified implementation task because it has several machine learning inbuilt libraries and classes with deployable tools which can be achieved through few lines of codes been optimized to achieve its best performance level.

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