INCORPORATION ARTIFICIAL INTELLIGENCE FEATURES IN HUMAN RESOURCES MANAGEMENT FOR EFFECTIVE EMPLOYEES RECRUITMENT

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Abstract - E-recruitment represents an innovative technological approach to selecting one of an organization's most valuable assets: its human capital. However, it is essential to acknowledge that managing timelines can be particularly challenging in a highly competitive labour market and that the e-recruitment process inherently faces certain difficulties. To overcome this problem, a novel catboost Sequence neural intelligence System (CSNIS) is planned to build in this present research work for recruiting suitable employees in each career.In the preliminary stage, the Human Resources (HR) database was populated with data regarding employees' qualifications, career aspirations, and overall sentiments, which were subsequently utilized to train the Python system. Following this, a process of filtering and feature analysis was conducted to evaluate and identify the career-related attributes. Subsequently, employee qualifications were aligned with job descriptions, leading to the identification of appropriate career paths for each employee based on the derived decisions. Finally, key metrics such as R-squared, Mean Absolute Error (MAE), accuracy, Mean Squared Error (MSE), f1-score and Root Mean Squared Error (RMSE) were computed and compared against other models.

Keywords - Human Resources, Recruitment, Feature Selection Process, Catboost, Filtering.

I. INTRODUCTION

Artificial intelligence possesses the capability to greatly enhance human resources processes and optimize the tasks associated with recruitment and personnel management [1]. AI serves a valuable purpose beyond merely handling operational and administrative tasks; it also facilitates the acquisition of profound insights related to strategic planning [2]. While the capacity of AI to improve HR functions is generally recognized, there remains a degree of uncertainty regarding its effective application and the optimization of its capabilities [3].Artificial Intelligence (AI) has emerged as a transformative influence across various sectors, [4], with previously unheard-of potential to improve decision-making and expedite procedures [5]. AI is transforming HR procedures [6], including hiring, managing talent [7], and assessing employee performance. Organizations may maximize workforce performance and efficiency by utilizing AI to automate repetitive operations [8], analyze massive volumes of data quickly and accurately, and produce meaningful insights. The potential for greatly increased operational savings exists with the integration of AI in HR [9]. AI-driven algorithms, for instance, can analyze numerous resumes and identify the most suitable candidates according to established criteria.This approach is more efficient in terms of both time and cost when contrasted with manual screening methods [10].Another important area in HR where AI has a significant impact is performance enhancement [11]. Organizations can obtain deeper insights into employee performance indicators with AI-driven analytics [12], which can also help discover patterns and trends that traditional techniques might miss [13]. In addition to supporting more objective performance reviews, this data-driven method also enables customized feedback and development plans catered to the specific requirements of each employee [14]. Furthermore, AI-powered predictive analytics may project future labour needs, assisting HR departments in anticipating staffing requirements, succession planning, and skill gaps [15]. This helps HR departments better match their human capital strategies with corporate goals. However integrating AI into HR is not without its difficulties [16], The matter of bias in AI algorithms represents a significant ethical concern, particularly regarding moral dilemmas [17]. AI systems acquire knowledge from historical data, which can encompass biases stemming from earlier performance evaluations or recruitment choices [18]. If these prejudices are not appropriately addressed, they have the potential to exacerbate already-existing inequality and provide unfair results when it comes to hiring [19], advancement, and pay. To ensure fair and equal outcomes for all employees [20], proactive methods including varied data sourcing, algorithmic transparency [21], and ongoing monitoring are necessary for mitigating bias in AI [22].Accountability and transparency are also essential components of implementing AI in HR. Stakeholders and employees want to know that judgments made by AI are transparent [23], dependable, and equitably determined. To preserve confidence in HR practices, it is imperative to provide systems for monitoring and evaluation [24], guarantee explainable AI models, and establish explicit standards for AI deployment. Furthermore, it is crucial to implement stringent validation procedures to guarantee the validity and

dependability of AI algorithms [25]. Testing AI models against various datasets to assess their dependability, accuracy, and performance in practical applications is known as algorithm validation [26]. This validation procedure helps reduce the hazards associated with biased or incorrect decision-making in addition to enhancing the robustness of AI systems [27]. Moreover, AI also makes it possible to implement customized performance management strategies that are suited to the demands of each employee [28]. Conventional performance evaluations frequently have biases and subjectivity. However, AI-driven systems may offer unbiased judgments based on measurable facts [29], which lessens the impact of human prejudices and enhances the dependability and fairness of performance reviews [30]. Achieving a delicate equilibrium between innovation and accountability is essential to fully harness the potential of artificial intelligence while addressing its ethical implications [31]. Through the adoption of moral values and the conscientious and responsible integration of AI into HR procedures [32], companies can leverage its advantages while preserving the welfare and entitlements of their personnel.

The key contribution of this work is defined as follows

- In the initial phase, the HR database including employee qualification, career aims and general emotions was collected and trained to the Python system
- Consequently, a novel CSNIS was designed with suitable intelligent prediction behaviour
- Henceforth, filtering and feature analysis have been performed for analyzing and selecting the career-related features
- Then based on the job description, the employee qualifications were matched and the suitable career for every employee was made based on the decision
- At final, the key parameters like R-square, MAE, MSE, and RMSE have been calculated and compared with other models

The document is structured into several key sections. Section 2 provides an in-depth review of the current literature, whereas Section 3 details the design of the system. Section 4 outlines the solution developed for the specific scenario. Section 5 assesses the results of the validated individual solutions. Lastly, Section 6 provides a summary of the conclusions.

II. RELATED WORKS

Some of the recent literature is defined as follows,

Huang et al. [33] introduced the innovative concept of personalized human resource management (HRM). This approach posits that the mechanical and analytical intelligence required for the implementation of personalized HRM initiatives is linked to the adoption of artificial intelligence.This development can be accredited to the benefits offered by high-performance work practices,in terms of productivity, a positive HR environment, flexibility, the return on HRM investment, and the financial performance of the company. This paper, for instance, does not address how the efficacy of customized HRM differs among employee categories. The drawbacks and restrictions of customized HRM, the introduction of moderators, and scenarios where conventional HRM techniques yield better results are all covered.

Kaushal et al [34]. The goal isto develop an integration of HRM and AI within the framework of diverse organizational roles and procedures. The suggested system offers the V integration into a range of HRM processes encompassing various activities such as recruitment, candidate assessment, orientation, training and development, performance appraisal, talent sourcing, management, and employee retention. The disadvantages of human resource management AI may result in unfair hiring practices, skewed performance reviews, and ultimately, a workforce with less diversity. The firm must have a multifaceted strategy to effectively counter these competitors.

W. Rodgers et al [35] have established a framework addressing the accountability and intelligence involved in AI-driven decision-making within human resource management. This conceptual model delineates the decision-making processes of individuals operating within an algorithmic context of human resource management.The model illustrates the influence of perceptions, evaluations, and information utilization on the process of strategy selection.The method has a drawback in that AI-driven insights offer perceptions into the dynamics of the workforce, facilitating data-driven talent management decision-making.

Chen et al [36]suggesteda framework for using AI technology to address management and training challenges then AI implementations in management reaction and training. The benefits of AI-based applications are improved decisions, increased production and efficiency, and better services. This study analyses the challenges faced by concerns about data security and privacy could lower employment.

U Murugesan et al [37] have approached a digitalization of a conceptual framework for HRM utilizing Artificial Intelligence, analyzed through the lens of Moment Structures. The suggested system offers the limitation are As AI takes over more HR tasks, there's a chance that some HR specialists could become unemployed.A quantitative approach could also be employed to examine the numerical impact of

AI-driven human resource decisions on employee turnover and organizational performance.

III. SYSTEM MODEL WITH PROBLEM STATEMENT

There is a great deal of promise for boosting corporate profitability from the sharp rise in AI applications in workplaces across the globe. AI is still a relatively new component of HRM, and several managers still lack basic knowledge of the technology. One of the corporate domains where AI implementation is trailing is HR. Moreover, AI's effects on workplace results upon closer inspection, the literature from the previous 20 years is insufficient to offer a comprehensive scientific overview of this corpus of work AI systems enhance organizational performance and capture the attention of decision-makers; however, they also pose a threat to the job security of human resources personnel. Human resource managers responsible for managing the processes of AI adoption face significant challenges. To address this issue, a novel approach has been developed.

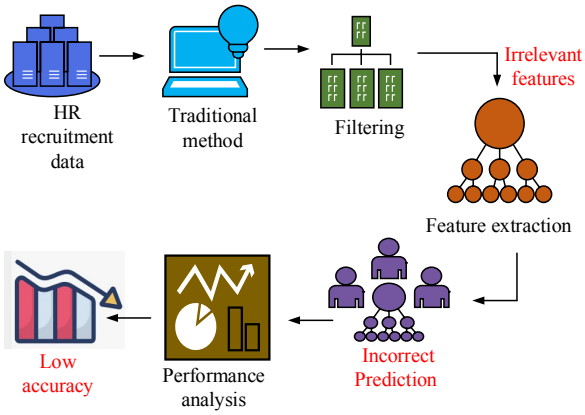


Fig.1 Limitation of traditional methods

The shortcomings of conventional prediction methods are illustrated in Figure 1. The current approaches necessitate the extraction of irrelevant features for prediction, which results in an inaccurate prediction process. Furthermore, the accuracy of these predictions is notably low, and they demand a considerable amount of computational time. To address these issues, the implementation of more sophisticated methods is essential.

IV. PROPOSED METHODOLOGY

The present research has introduced the recruitment and selection objectives from the use of hybrid intelligent models. A novel catboost Sequence neural intelligence System (CSNIS) is planned to build in this present research work for recruiting suitable employees in each career. The prime functions like filtering features selection and prediction have been performed. Furthermore, the HR career employee selection database (employees' qualifications, career aim and general emotions) was considered for this study to value the robustness of the proposed system. Here, based on the qualification of the employee, asuitable job career has been predicted. Finally, the performance parameters were measured and compared with other models.

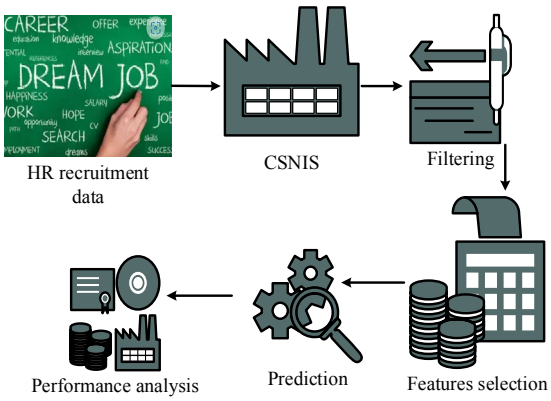


Fig.1 Proposed architecture

The architecture presented is illustrated in Figure 1. Initially, the dataset about recruitment data was utilized and trained within the Python environment. Furthermore, the developed methodology consisted of multiple stages, including filtering, feature selection, and prediction. During the filtering stage, irrelevant features were eliminated, which was succeeded by a comprehensive selection of the relevant features. The algorithm was then optimized, leading to enhanced accuracy.

4.1 Process of Proposed CSNIS

The structured framework employed the Catboost model alongside a sequence neural architecture. This methodology comprised five distinct stages: data training, hidden layers, feature selection, prediction, and output layers. Each layer represents a sequential component of the proposed model. The approach effectively identified both eligible and ineligible candidates within the recruitment dataset.

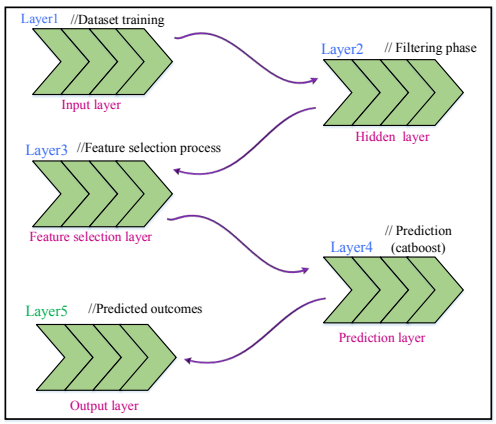


Fig. 3 Layers of CSNIS

The recruitment data was imported into the dataset by the data training layer during the data initialization phase. Subsequently, the filtering function within the

hidden layer performed the noise filtering process. The feature selection layer was responsible for the feature selection process. The features that were selected were utilized in the prediction layer, leading to the generation of accurate recruitment analysis in the output layer. The framework process illustrated is presented in Figure 3.

4.1.1 Data initialization

In the preliminary stage, the HR database gathered information about employees, encompassing their qualifications, career aspirations, and overall sentiments. This information was subsequently input into a Python-based system to train a machine-learning model. The data initialization function can be represented in Equation (1).

$$I(Dt) = (D_1, D_2, D_3, ...D_n) \quad (1)$$

Here, I denotes the initialization variable, Dt the variables, $|(D_1, D_2, D_3)$ the training variables, Dn and the number of data in the dataset.The initialization process was completed with the input layer. Following the completion of this process, the filtering process commenced.

4.1.2 Filtering

Filtering is a technique used to remove extraneous data, including unnecessary whitespaces, brackets, and tags, from a dataset before the training of a machine learning model.This process decreases the dimensionality of the data, resulting in quicker training durations and leading to more reliable results in intelligent systems.The filteringprocess can be represented in Equation (2).

$$F = T(Dt - Nf) \quad (2)$$

Here, F denotes the filtering process variable, T represents the variable used for tracking noise, Dt signifies the dataset that has been trained, and Nf indicates the noise features present within the dataset.The filtering procedure was carried out utilizing the hidden layer. Subsequently, the feature selection process began.

4.1.3 Feature selection

The process of feature selection is crucial in identifying professional pathways by utilizing the sequence neural network.Identifying and utilizing only the most pertinent career-related attributes, such as employee qualifications, years of experience, and career pathways, enhances predictive accuracy.The process of feature selection can be expressed through Equation (3).

$$Fs = m([Dt - a] - Ef) \quad (3)$$

Where, m signifies the current data, Ef indicates the features that have been extracted, Fs refers to the variable associated with feature selection, a represents the tracking variable, and Dt denotes the dataset. This CSNIS methodology simplifies unnecessary complexities, decreases the likelihood of overfitting, and enhances the model's capacity to generalize effectively among various employees.Effective feature selection allows the neural network to identify the most important time-dependent relationships, resulting in accurate predictions of careers and goals.

4.1.4 Prediction

The results of the feature selection process are input to the prediction system. Based on the feature selection results the catboost model plays an important role in determining the most suitable candidate for a position.Moreover, the model improves the accuracy of predictions.The process of making predictions can be expressed through Equation (4).

$$P = \begin{cases} if\,(Fs \geq 1) & eligible\ candidate \\ if\,(Fs < 0) & not\ eligible\ candidate \end{cases} \quad (4)$$

Where the variable P represents the prediction.The expected characteristics that are equal to or greater than 1 imply that the candidate satisfies the eligibility criteria, while a projected characteristic that is below 0 signifies that the candidate does not fulfil the eligibility requirements.

Algorithm: 1 CSNIS
Start
{
Data initialization ()
{
$\text{int}, I(Dt), D_1, D_2, D_3, D_n$
// The process variables are being initialized
$I(Dt) = (D_1, D_2, D_3, ...D_n)$
//The variables involved in the initialization process are set up
}
filtering ()
{
$\text{int}\ F, T, Dt, Nf$
// Begin by setting up the variables required for filtering
$Filtering \rightarrow noise\ features\,(Nf)$
//The filtering variables have been initialized
}
Feature selection ()
{

int Fs, m, Dt, a, Ef
//Set up the variables for feature selection
$Fs = m([Dt - a] - Ef)$
//The variables for feature selection have been initialized
}
Prediction ()
{
$if\,(Fs \geq 1)$
Eligible candidate
$if\,(Fs < 0)$
Not eligible candidate
// based on the selected features the eligible candidates are recruited
}
}
Stop

Figure 4 offers an in-depth examination of the sequential procedures necessary for the implementation of the developed framework. Following this, the algorithm introduces the pseudocode that aligns with the intricate mathematical formulation detailed in Algorithm 1.

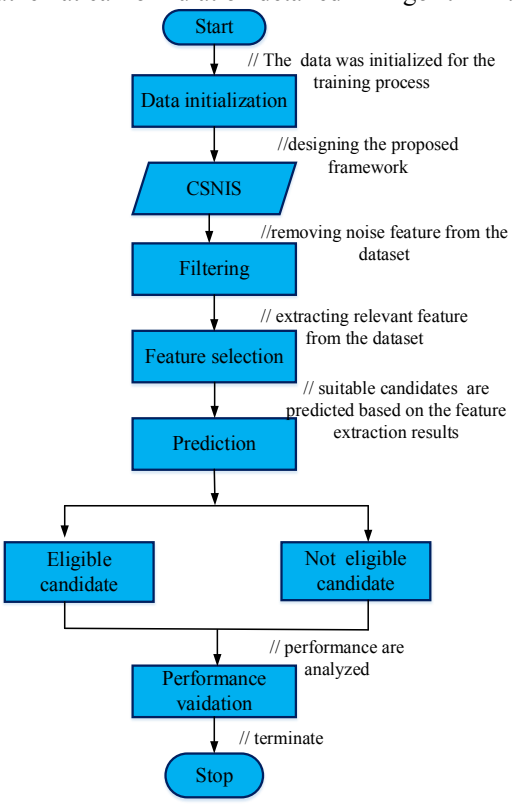


Fig.4 Flow chart of CSNIS

V. RESULT AND DISCUSSION

The CSNIS novel has been created and implemented within the Python environment. Initially, the computer was employed to collect and train the recruitment dataset. The software was tailored to function on the Windows 10 operating system, utilizing Python as its core framework. The efficacy of the customized model was confirmed through a comprehensive case study. Subsequently, the outcomes of the implemented model were compared with the existing model to demonstrate improved performance and determine the percentage of enhancement. Table 1 presents the operational variables.

Parameter	Specifications
Programming language	Python
OS	Windows 10
Version	3.7.6
Data count	1500
Network	Sequence neural

Table1 implementation parameters

5.1 Case study

To assess the efficacy of the developed methodology, a series of validation tests were conducted, and the results were systematically organized. A case study was performed to assess the effectiveness of the established framework. The efficacy of the constructed model is examined utilizing the innovative CSNIS. Additionally, the datasets are utilized to assess the performance metrics of the models that have been developed.The dataset aboutrecruitment data [39]was sourced from the official Kaggle platform.

A new CSNIS approach has been established for predicting cotton leaf disease, utilizing a dataset comprising 1500 samples to examine the processes of predicting the suitable employee. Additionally, results were obtained concerning data filtering for predictionand feature selection.The dataset was also enhanced to remove any extraneous noise features. The procedure of feature extraction, which entails the identification of pertinent features from the dataset, is crucial for predicting the suitable employee.

Total samples:1500	
Eligible	465
Not eligible	1035
Training samples (80%): 1200	
Eligible	380
Not eligible	820
Testing samples (20%):300	
Eligible	85
Not eligible	215

Table2 dataset details

The suggested methodology also seeks to accurately differentiate between eligible and not-eligible candidates.The dataset comprises a total of 1,500 data points, of which 1,200 are allocated for training purposes and 300 for testing. The specifics of the dataset are outlined in Table 2.

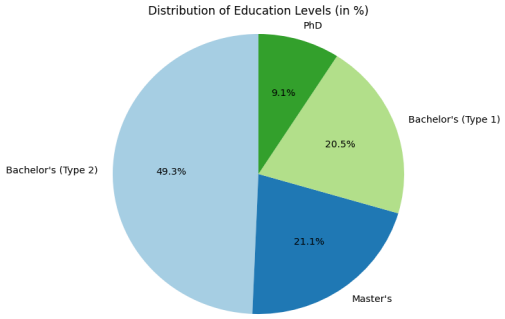


Fig.5 Distribution of education levels

The analysis of educational attainment within the recruitment process illustrates the qualifications of applicants. Individuals holding PhDs represent 9.1% of the total, indicating a limited number of highly specialized candidates, which may be desirable for research or advanced positions. Collectively, candidates with Bachelor's degrees (Type 1 and Type 2) comprise 69.8%, suggesting that a significant portion of applicants possess essential knowledge applicable to a range of roles. Type 1 Bachelor's degrees, accounting for 20.5%, likely pertain to specific disciplines, whereas Type 2 degrees, at 49.3%, may reflect a more generalized educational background. Furthermore, those with Master's degrees constitute 21.1%, underscoring a considerable presence of candidates with advanced expertise, which is attractive for positions demanding specialized knowledge. This educational distribution indicates a varied talent pool, with a notable emphasis on Bachelor's and Master's degrees, highlighting the diverse job requirements and the critical role of educational qualifications in the recruitment process.Figure 5 depicts the distribution of educational attainment levels.

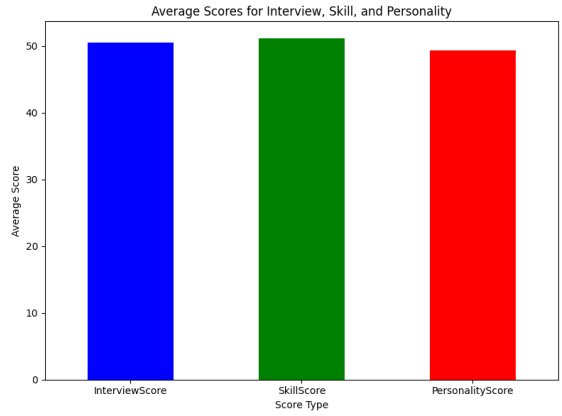


Fig.6 Average score for interview, skill, personality

The average scores obtained from interviews, skills assessments, and personality evaluations during the recruitment process offer valuable insights into a candidate's suitability. The Interview Score, typically the highest, indicates candidates' performance in direct evaluations, reflecting their communication skills and compatibility with the company culture. The Skill Score measures the candidates' technical or job-specific abilities, which are vital for assessing their capacity to fulfil the responsibilities of the position. The Personality Score examines characteristics such as teamwork, adaptability, and work ethic, which are essential for ensuring alignment with the organization's values. A comprehensive assessment that balances these scores highlights a well-rounded evaluation strategy, focusing not only on technical expertise but also on interpersonal and personality traits. Candidates who achieve higher scores across all three dimensions are more likely to be deemed eligible, presenting a well-rounded profile that fits the role.Figure 6 depicts the average scores for interviews, skills, and personality assessments.

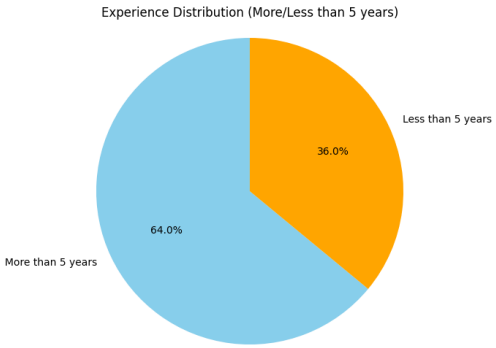
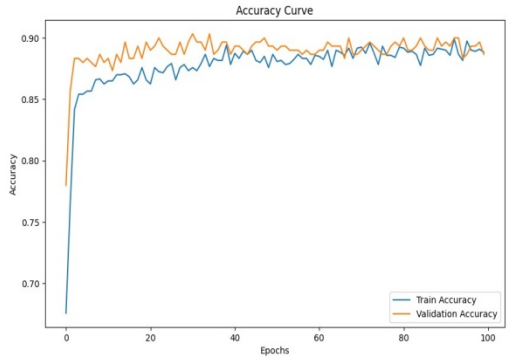
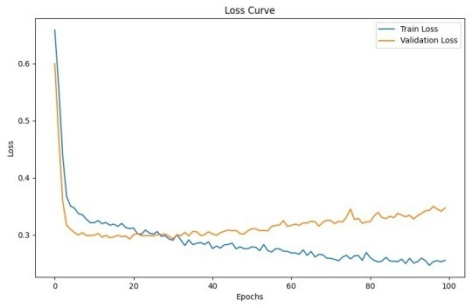


Fig.7 years of experience

The distribution of experience within the recruitment process reveals that 36.0% of candidates possess less than 5 years of experience, while 64.0% have more than 5 years. This distinction underscores the eligibility criteria for various positions. Candidates with over 5 years of experience are frequently regarded as more qualified due to their comprehensive knowledge and capability to manage complex tasks, rendering them attractive for senior or specialized roles. In contrast, the 36.0% with under 5 years of experience may be suitable for entry-level or junior positions, where potential and adaptability may be prioritized over extensive experience. This distribution indicates a recruitment strategy that appreciates both seasoned professionals and emerging talent, enabling the organization to harmonize the innovative contributions of younger candidates with the stability and expertise offered by more experienced individuals. The focus on varying levels of experience significantly impacts candidate eligibility, thereby influencing the dynamics of the organization's workforce.Fig. 7 depicts the years of experience.



A)



b)

Fig.8 A) accuracy, B) loss

Figure 8 presents the validation graphs for accuracy and loss. The significance of loss and accuracy curves in evaluating a model's performance during both the training and testing phases cannot be overstated. The accuracy curve serves as a visual depiction of the model's effectiveness, with the red line representing training accuracy and the green line indicating evaluation accuracy. As the model improves its predictions and classifications, it achieves favourable results. Notably, the accuracy curve for the developed method exceeds that of conventional techniques, underscoring its benefits.

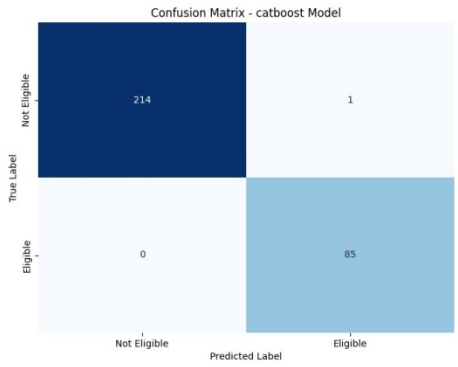


Fig.9Confusion matrix

The confusion matrix presented in Fig. 9details the results of confusion matrices across four categories within a test dataset, indicating the counts of false positives (FP),true negatives (TN) true positives (TP), and false negatives (FN), for each category. The model successfully made accurate predictions for two categories, with no instances of not-eligibility and one instance of eligibility. Furthermore, the model demonstrated its ability to predict outcomes accurately within the evaluation dataset.

5.2 Performance Analysis

The performance scoring process involves evaluating essential metrics such as F1-score,accuracy, MSE, MAE, R-square, and RMSE, which are commonly employed to assess the effectiveness of models. These metrics validated the model's predictive abilities. This approach ensures that the new model surpasses prior performance, adhering to expectations set by these metrics. Current models, such as. Which are commonly employed to assess the effectiveness of models. These metrics validated the model's predictive abilities. This approach ensures that the new model surpasses prior performance, adhering to expectations set by these metrics. Current models, such as. K nearest neighbour (K-NN) [38], Support Vector Machine (SVM) [38], Logistic Regression (LG) based on Avant optimization [38], and LG based onapres optimization [38].

5.2.1 Accuracy

Evaluating the method's accuracy is crucial for measuring its predictive performance. The accuracy is determined by the proportion of correct predictions relative to the overall number of predictions made. This ratio helps in determining how well the method can produce reliable and precise results. Eqn. (5)provides the mathematical formula for calculating accuracy.

$$Accuracy = \frac{Tp + Tn}{Tn + Fp + Fp + Fn} \quad (5)$$

Where, Tp and Tn Indicate the correctly identified positive and negative values, respectively. Meanwhile, Fp , Fn Consider the results that are classified as false positives and false negatives.

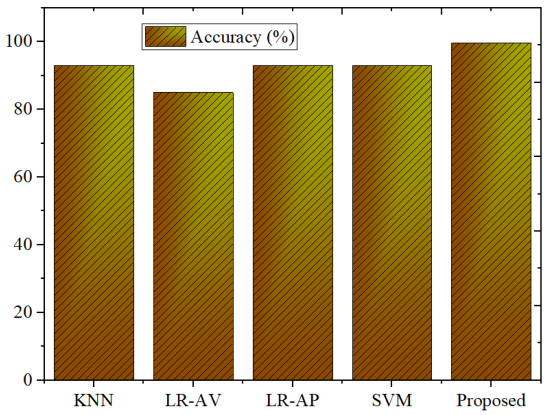


Fig.10 Comparison of accuracy

Fig.10 illustrates a comparison of accuracy among various models. The analysis reveals the percentage of correct predictions for each model. KNN, LR-AP, and SVM each attained an accuracy of 95%, reflecting comparable levels of effectiveness. In contrast, LR-AV exhibited a lower performance with an accuracy of 85%. The current method achieved the highest accuracy at 99.6%, showcasing its superior classification capabilities relative to the other models.

5.2.2 F1-score

The model's performance is assessed through the standard averaging of recall and precision, ensuring a balanced trade-off between the two metrics. This approach is especially valuable in scenarios with imbalanced classes. The integrated metric offers an extensive perspective on the model's capacity to identify pertinent instances while minimizing false positives. Equation (6) is used to calculate this metric.

$$F1-score = 2\left(\frac{P*R}{P+R}\right) \tag{6}$$

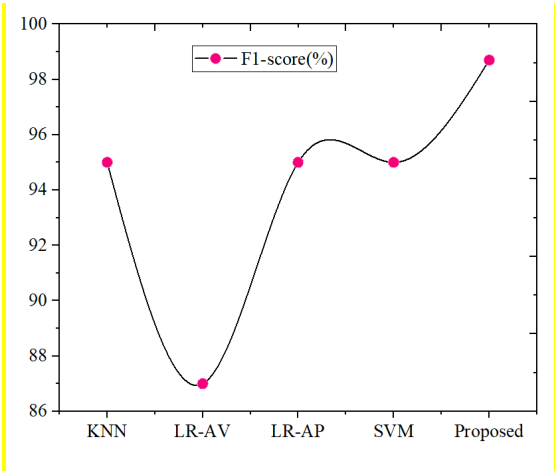


Fig.11 Comparison of F1-score

Fig.11 presents a comparison of F1scores, which assesses the performance of various classification models. The KNN, LR-AV, and SVM all attained comparable scores of 95. Additionally, LR-AP also achieved a score of 95. In contrast, the current method surpassed all other models, achieving an F1-score of 99.4, thereby demonstrating a superior equilibrium between precision and recall.

5.2.3 MAE

MAE is determined by calculating the mean difference between the significant values in the dataset and the plotted values. The MAE calculation is described in Eqn. (7).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left(Ai - Pi\right) \tag{7}$$

Here, n denotes the number of test samples, Ai indicates the actual data, Pi and signifies the predicted data.

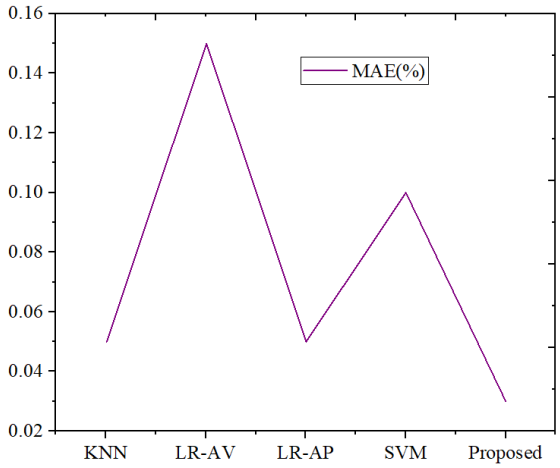


Fig.12Comparison of MAE

Fig.12 illustrates a comparison of the MAE, which emphasizes the average size of errors in the predictions. Both KNN and LR-AP recorded a low MAE of 0.05, reflecting comparable performance levels. In contrast, SVM exhibited a higher error rate of 0.1, and LR-AV had the highest error at 0.15. Notably, the created method surpassed all other approaches with the lowest MAE of 0.03, signifying the most precise and reliable predictions.

5.2.4 MSE

The MSE serves as a metric that quantifies the average of the squared discrepancies between the actual and estimated values. The MSE calculation is described in Eqn. (8).

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Ai - Pi\right) \tag{8}$$

Here, Ai represents the actual data, Pi denotes the predicted data.

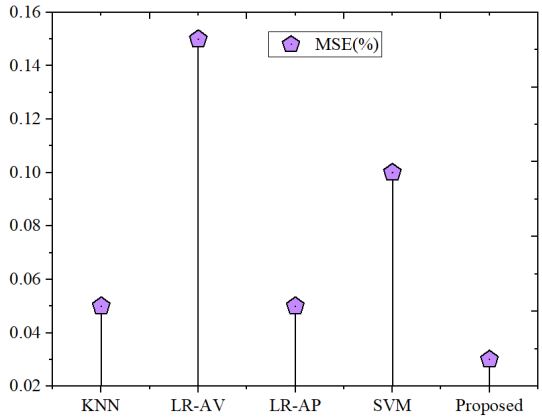


Fig.13 Comparison of MAE

Fig.13 illustrates a comparison of MSE.This evaluates the extent to which the predictions made by

each model correspond with the actual values. Both KNN and LR-AP attained a commendable MSE of 0.05, signifying strong identified accuracy. In contrast, SVM exhibited a marginally higher error rate of 0.1, and LR-AV demonstrated inferior performance with an MSE of 0.15. Notably, the proposed method achieved the lowest MSE of 0.03, indicating superior predictive capability.Table 3 presents a comparison with existing models.

Methods	Accuracy	MSE	F1-score	MAE
KNN	95	0.05	95	0.05
LR-AV	85	0.15	87	0.15
LR-AP	95	0.05	95	0.05
SVM	95	0.1	95	0.1
PROPOSED	99.6	0.03	99.4	0.03

Table3Comparison with existing models

5.2.5 R-square

R-squared is a statistical measure that measures the proportion of the variance in the dependent variable that is accounted for by the independent variable in a regression model. The R-squared calculation is described in Eqn. (9).

$$R^2 = 1 - \frac{RSS}{TSS} \tag{9}$$

Here, RSS represents the regression number of squares, TSS and denotes the sum of all squares. For the performance scenario, the R^2 metrics were act based on the exact forecasting scenario.The approach that was developed attained an R-square value of 98.3%, signifying that the model accounts for nearly all the variability present in the data.

5.2.6 RMSE

The model's predicted values are assessed against the actual values, and the average discrepancy between the two is computed.The calculation of RMSE is outlined in Equation (9).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(Ai - Pi\right)} \tag{10}$$

Here, Ai denotes the actual data, Pi denotes the predicted data, n denotes the number of test samples.The suggested approach, with an RMSE of 5.77, indicates a slight average deviation between the predicted and actual values.

5.3 Discussion

A novelCSNIS is planned to be built for recruiting suitable employees.This section of the research confirmed enhanced performance based on comparative analyses. Furthermore, the stability score of the model was calculated and compared with those of current models to assess its effectiveness. Information concerning the performance of CSNIS is provided in Table 4.

Metrics	Percentages (%)
R-square	98.3
MAE	0.03
MSE	0.03
RMSE	5.77
Accuracy	99.6
F1 score	99.4

Table4Performance of the proposed

The new approach exhibits exceptional performance across a range of metrics. It attained an R-square value of 98.3%, signifying that the model accounts for nearly all the variance present in the data. The model's predictions demonstrate exceptional accuracy, as evidenced by the low MAE of 0.03 and MSE of 0.03. Furthermore, the RMSE of 5.77 demonstrates a minimal average discrepancy between the predicted and actual values. Furthermore, the method demonstrates an impressive accuracy rate of 99.6% and an F1-score of 99.4%, indicating a remarkable balance between precision and recall, which makes it exceptionally effective for classification tasks.

VI. CONCLUSION

This study focused on the development and implementation of theCSNIS, a system specifically designed torecruit suitable employees.Furthermore, an assessment of the anticipated outcomes of the created model was conducted and compared with alternative methods.The performance analysis indicates that the created model has attained a greater stability ratecompared to the existing models. Additionally, an extensive case study has confirmed the effectiveness of the established model. Subsequently, the developed model will be evaluated based on various assessment criteria, including R-square, MAE, MSE, RMSE, Accuracy, and F1 score.The innovative method achieves an R-square of 98.3%, indicating strong predictive power. Its low MAE of 0.03 and MSE of 0.03 reflect high accuracy, while the RMSE of 5.77shows minimal deviation from actual values. With an accuracy of 99.6% and an F1-score of 99.4%, the method is highly effective in classification, balancing precision and recall.Future investigations should consider the integration of multi-criteria decision-making frameworks to enhance the recruitment process for intricate positions. Moreover, the automation of feedback mechanisms for ongoing system enhancement represents another area with considerable potential.

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