Optimizing Recruitment: Harnessing Machine Learning for Predictive Hiring Decisions

Dileep Malothu
The Richard DeVos Graduate School of Management
Northwood University
Midland, Michigan, USA
malothud114@northwood.edu

Harika Yenuga
The Richard DeVos Graduate School of Management
Northwood University
Midland, Michigan, USA
yenugah80@northwood.edu

Mukhesh Ravi
The Richard DeVos Graduate School of Management
Northwood University
Midland, Michigan, USA
ravim@northwood.edu

Saketh Banda
The Richard DeVos Graduate School of Management
Northwood University
Midland, Michigan, USA
bandas76@northwood.edu

***Abstract*— This study explores the application of machine learning models to optimize recruitment processes by predicting hiring decisions based on candidate profiles. The primary objective is to develop a predictive model that classifies candidates as 'hired' or 'not hired' using demographic information, qualifications, and recruitment scores. The dataset comprises 1,500 candidates with features such as age, gender, education level, work experience, and skill scores. Various machine learning algorithms, including Random Forest, Support Vector Machine, Logistic Regression, and advanced ensemble methods like CatBoost and XGBoost, were employed to identify the most effective model. CatBoost emerged as the top-performing model with an accuracy of 95%, followed by Random Forest and XGBoost. The study highlights Recruitment Strategy, Education Level, and Personality Score as the most influential factors in hiring decisions. The findings suggest that leveraging machine learning can streamline recruitment, reduce biases, and improve hiring outcomes. Future research should focus on enhancing model performance, mitigating biases, and validating the model in real-world scenarios.**

***Keywords*— Machine Learning, Predictive Hiring, Recruitment, CatBoost, Hyperparameter Tuning, Classification & Modelling**

I. Introduction

Recruitment is a critical function for organizations, directly impacting their productivity and success. Traditional recruitment processes often involve significant time and resources, with the risk of human biases influencing hiring decisions. In recent years, machine learning has emerged as a powerful tool to enhance recruitment strategies by providing data-driven insights and automating decision-making processes. By analyzing candidate attributes such as education, skills, and experience, machine learning models can predict hiring outcomes, help organizations make more informed and equitable hiring decisions. This study investigates the use of various machine learning algorithms to predict hiring decisions, aiming to optimize recruitment processes and improve overall hiring efficiency.

A. Problem Statement

This project aims to predict the hiring decision of candidates based on their demographic information, qualifications, and scores in recruitment processes. The goal is to help streamline recruitment decisions by building a machine learning model that can classify candidates as either 'hired' or 'not hired' based on their profile data.

B. Objective

The objective of this study is to investigate the use of machine learning models to predict hiring decisions based on various candidate attributes, such as education level, skill score, and work experience. By analyzing these features, the study aims to identify the key factors that contribute to successful hires and develop predictive models that can help organizations optimize their recruitment strategies, reduce biases, and improve overall hiring outcomes.

C. Significance

Hiring the right candidates is not just about filling positions; it directly impacts organizational productivity and success. A poor hiring decision can result in substantial costs due to training, lost productivity, and turnover. Leveraging machine learning models to predict hiring outcomes can significantly streamline the recruitment process by identifying key factors that lead to successful hires. Moreover, it can help mitigate biases and ensure a fairer, more efficient evaluation process. This research explores how data-driven approaches can assist organizations in making more informed, equitable, and accurate hiring decisions.

D. Research Question

The central question guiding this research is: Which factors are most predictive of hiring decisions, and how can machine learning models be employed to enhance recruitment strategies? By examining features such as education, skill scores, and work experience, this study aims to build predictive models that assist in automating and optimizing the recruitment process.

E. *Literature Review*

This paper focuses on developing a predictive model to classify candidates as 'hired' or 'not hired' using various machine learning algorithms. The primary objective is to streamline recruitment processes, reduce biases, and improve hiring outcomes. In contrast, the first paper, "Recruitment in the Times of Machine Learning" by Karolina Rąb-Kettler and Bada Lehnervp, explores the impact of socio-economic changes and technological advancements on human resources management, particularly emphasizing humanistic management and the role of AI in recruitment. This paper discusses the theoretical frameworks of humanistic management and highlights the potential of AI to reduce biases while warning against the risks of technological unemployment.

The second paper, "Human-Centric Multimodal Machine Learning: Recent Advances and Testbed on AI-Based Recruitment" by Alejandro Peña et al., investigates biases in AI-driven recruitment systems and proposes methods to ensure fairness and transparency in automated decision-making processes. It introduces a multimodal learning framework combining image, text, and structured data to evaluate biases in recruitment algorithms, using pre-trained models like ResNet-50 for image analysis and BiLSTM for text analysis, along with fairness-aware learning techniques.

Based on our analysis, CatBoost as the top-performing model with an accuracy of 95%, highlighting Recruitment Strategy, Education Level, and Personality Score as the most influential factors in hiring decisions. In contrast, the first paper emphasizes the importance of humanistic management in recruitment, advocating for a balance between technological advancements and human-centric approaches. The second paper demonstrates that common machine learning models can inadvertently learn and amplify biases present in the training data. It introduces the FairCVtest framework to study and mitigate these biases, showing that removing sensitive information can improve fairness in automated recruitment systems.

In terms of applications and implications, your paper suggests that leveraging machine learning can streamline recruitment, reduce biases, and improve hiring outcomes, calling for future research to enhance model performance and validate the models in real-world scenarios. The first paper advocates for a humanistic approach to recruitment, integrating AI to automate administrative tasks while ensuring that human values and ethical considerations remain central. The second paper focuses on the ethical implications of AI in recruitment, proposing methods to ensure transparency, accountability, and fairness, highlighting the importance of developing AI systems that are not only efficient but also socially responsible.

II. METHODOLOGIES

A. *Dataset Summary*

The dataset used in this study contains information on 1,500 candidates, with 11 features that capture various attributes, including age, gender, education level, work experience, and skill scores. The target variable, Hiring Decision, indicates whether a candidate was hired (1) or not hired (0). Table 1 provides a summary of the key features in the dataset.

TABLE I. SUMMARY OF FEATURES IN THE DATASET

Feature	Description	Data Type
Age	Age of the candidate	Numerical
Gender	0 = Male, 1 = Female	Categorical
Education Level	1 = Bachelor's (Type 1), 2 = Bachelor's (Type 2), 3 = Master's, 4 = PhD	Categorical
Experience Years	Years of professional experience	Numerical
Skill Score	Technical skill score (0-100)	Numerical
Personality Score	Personality fit score (0-100)	Numerical
Recruitment Strategy	1 = Aggressive, 2 = Moderate, 3 = Conservative	Categorical
Hiring Decision	0 = Not Hired, 1 = Hired	Categorical

B. *Preprocessing Steps*

1. Converting Numerical Variable to Categorical

Initial Data Type

```
Data Type:
Age                      int64
Gender                   int64
EducationLevel           int64
ExperienceYears          int64
PreviousCompanies        int64
DistanceFromCompany    float64
InterviewScore           int64
SkillScore               int64
PersonalityScore         int64
RecruitmentStrategy      int64
HiringDecision           int64
dtype: object
```

Update Data Type

```
Updated data types:
Age                       int64
Gender                 category
EducationLevel         category
ExperienceYears           int64
PreviousCompanies         int64
DistanceFromCompany     float64
InterviewScore            int64
SkillScore                int64
PersonalityScore          int64
RecruitmentStrategy    category
HiringDecision         category
dtype: object
```

Fig. 1 Data Type Conversion

In this step, we can analyse that Gender, Education Level, RecruitmentStrategy and HiringDecisin have 4 or less unique values in each of their respective column. As per the dataset, it is a numerical feature. It would be more insightful for us to convert these numerical values into categorical values.

2. Handling Missing Values or Duplicate Rows

```
Categorical Features:
['Gender', 'EducationLevel', 'RecruitmentStrategy', 'HiringDecision']
Number of Categorical Features: 4

Numerical Features:
['Age', 'ExperienceYears', 'PreviousCompanies', 'DistanceFromCompany', 'InterviewScore', 'SkillScore', 'PersonalityScore']
Number of Numerical Features: 7

Number of Missing Values:
0

Number of Duplicate Rows:
0
```

Fig. 2 Output from Initial Preprocessing Steps

Here, we have analyzed the dataset for any missing values and duplicate rows. There were no duplicate or missing values identified in this dataset. There are 1500 rows of data and 11 columns in this dataset. We also further checked on the number of categorical and numerical features.

3. Feature Scaling

```
# Verify the scaled data
print("Scaled Training Data (First 5 Rows):")
print(X_train_scaled[:5])

Scaled Training Data (First 5 Rows):
[[ 0.6457784   1.0168079   0.93165673 -0.79528254 -1.40574422  0.07718799
   0.34722025  0.99391022  0.17475903  0.14298599]
 [ 1.29707473  1.0168079   0.93165673 -1.00954815  0.01121761 -0.2057359
   0.76608358 -0.33002097  0.20881959  0.14298599]
 [ 0.86287717  1.0168079  -0.22448399  1.3473736   0.71969853  0.00299797
  -0.31598002 -0.49975573  0.17475903 -1.29888955]
 [-0.65681425 -0.98346994 -0.22448399  0.06177992  0.01121761  0.09564651
   1.0453258   0.07734248  1.02627293  1.58486153]
 [ 1.40562411  1.0168079  -0.22448399 -0.1524857   0.71969853 -0.79086217
  -0.80465391  0.68838764 -0.3361493   0.14298599]]
```

Fig. 3 Scaling the Training Data

To address the potential disparity in feature scales and ensure that all features contribute meaningfully to the model, we implemented feature scaling.

4. Descriptive Statistics for All Features

```
Summary Statistics for Numerical Features:
               Age  ExperienceYears  PreviousCompanies  DistanceFromCompany  \
count  1500.000000      1500.000000         1500.00000          1500.000000
mean     35.148667         7.694000            3.00200            25.505379
std       9.252728         4.641414            1.41067            14.567151
min      20.000000         0.000000            1.00000             1.031376
25%      27.000000         4.000000            2.00000            12.838851
50%      35.000000         8.000000            3.00000            25.502239
75%      43.000000        12.000000            4.00000            37.737996
max      50.000000        15.000000            5.00000            50.992462

       InterviewScore   SkillScore  PersonalityScore
count     1500.000000  1500.000000       1500.000000
mean        50.564000    51.116000         49.387333
std         28.626215    29.353563         29.353201
min          0.000000     0.000000          0.000000
25%         25.000000    25.750000         23.000000
50%         52.000000    53.000000         49.000000
75%         75.000000    76.000000         76.000000
max        100.000000   100.000000        100.000000

Summary Statistics for Categorical Features:
       Gender  EducationLevel  RecruitmentStrategy  HiringDecision
count    1500            1500                 1500            1500
unique      2               4                    3               2
top         0               2                    2               0
freq      762             740                  770            1035
```

Fig. 4 Summary Statistics of All Variables

We also further performed a descriptive statistic for all variables to know more about certain values and range. We identified the mean, standard deviation, minimum and maximum value, the 25th, 50th and 75th percentile for each numerical feature. For the categorical features, we performed a unique, top and frequency analysis.

5. Correlation Matrix

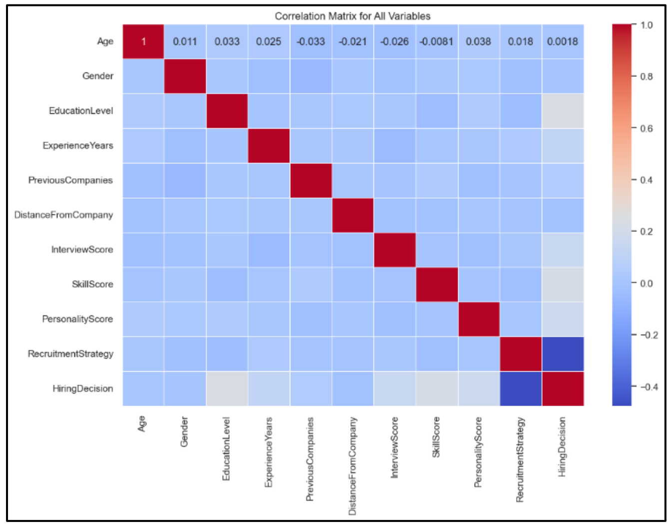

Fig. 5 Correlation Heatmap for All Variables

Based on the Correlation Heatmap, we can conclude that EducationLevel, SkillScore & PersonalityScore are the top 3 features that are correlated to the target variable. RecruitmentStrategy which has a score of – 0.477 shows a negative correlation with the target variable.

6. Gender Distribution in the Dataset

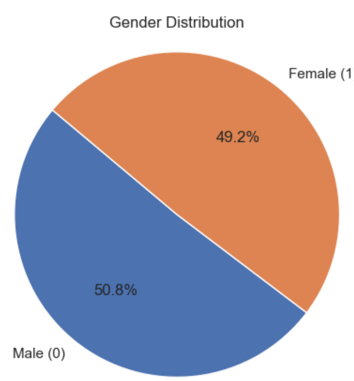

Fig. 6 Gender Distribution

C. Machine Learning Models

In this study, a variety of machine learning algorithms were chosen to ensure a comprehensive analysis of the factors influencing hiring decisions. Random Forest was selected due to its robust performance with complex datasets, as it constructs multiple decision trees and aggregates their predictions, reducing the risk of overfitting. Support Vector Machine

(SVM) was employed to test its ability to find a clear margin of separation between hired and non-hired candidates, particularly in cases where the data may not be linearly separable. Logistic Regression was chosen for its simplicity and interpretability, serving as a baseline model for binary classification. Additionally, Gradient Boosting, along with more advanced variants like XGBoost, LightGBM, and CatBoost, were included for their efficiency and high accuracy. These ensemble boosting methods iteratively correct prediction errors, making them particularly powerful for structured data. By comparing these diverse algorithms, the study aims to identify the most accurate and efficient model for predicting hiring outcomes.

Equation for CatBoost prediction model:

$$\hat{y}=\sum Ti=1\eta\cdot fi(x)$$

(T) is the number of iterations, (\eta) is the learning rate, and (f_i(x)) is the prediction of the (i)-th iteration.

III. Results

A. Model Accuracy Scores

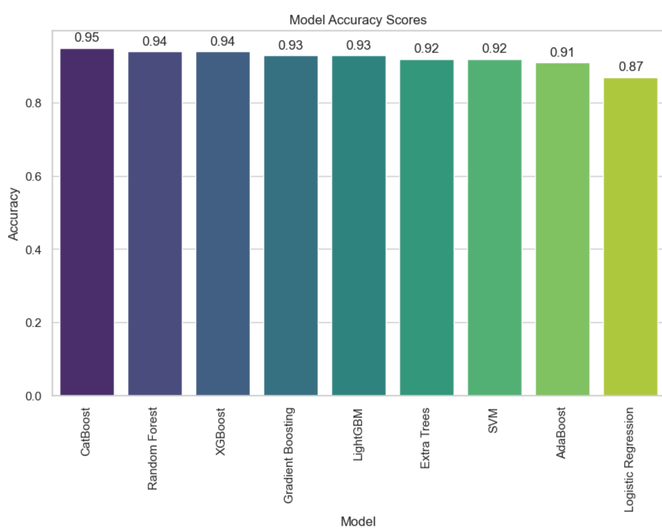

Fig. 7 Accuracy Scores across all models

B. Classification reports for TOP 3 models

- CatBoost

TABLE 2. CLASSIFICATION REPORT FOR CATBOOST

	Precision	Recall	F1 Score	Support
0	0.96	0.97	0.97	215
1	0.93	0.91	0.92	85
Accuracy			0.95	300
Macro Avg	0.95	0.94	0.94	300
Weighted Avg	0.95	0.95	0.95	300

- Random Forest

TABLE 3. CLASSIFICATION REPORT FOR RANDOM FOREST

	Precision	Recall	F1 Score	Support
0	0.95	0.98	0.96	215
1	0.94	0.86	0.90	85
Accuracy			0.94	300
Macro Avg	0.94	0.92	0.93	300
Weighted Avg	0.94	0.94	0.94	300

- XGBoost

TABLE 4. CLASSIFICATION REPORT FOR XGBOOST

	Precision	Recall	F1 Score	Support
0	0.95	0.96	0.96	215
1	0.90	0.88	0.89	85
Accuracy			0.94	300
Macro Avg	0.93	0.92	0.93	300
Weighted Avg	0.94	0.94	0.94	300

C. ROC-AUC Curves

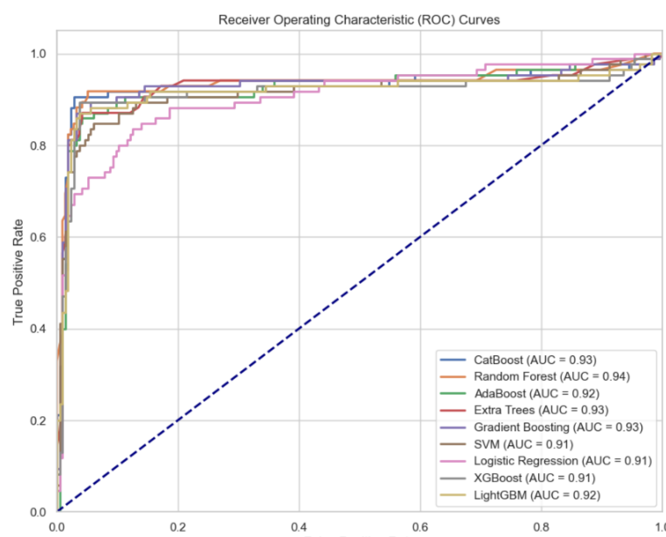

Fig. 8 ROC-AUC Curves for All Models

D. *Confusion Matrix*

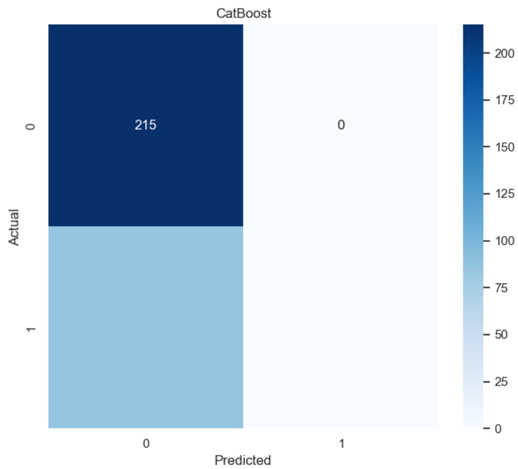

Fig. 9 Confusion Matrix for CatBoost Model

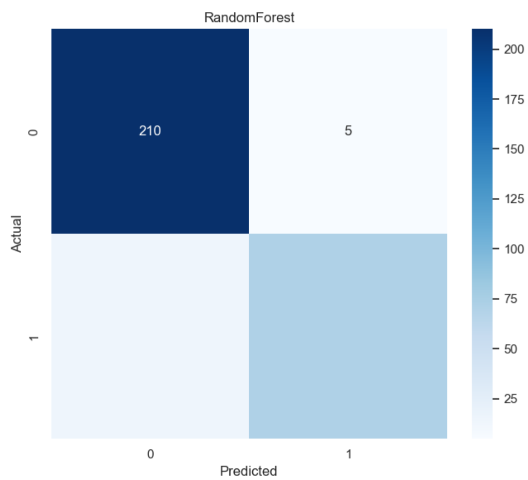

Fig. 11 Confusion Matrix for Random Forest

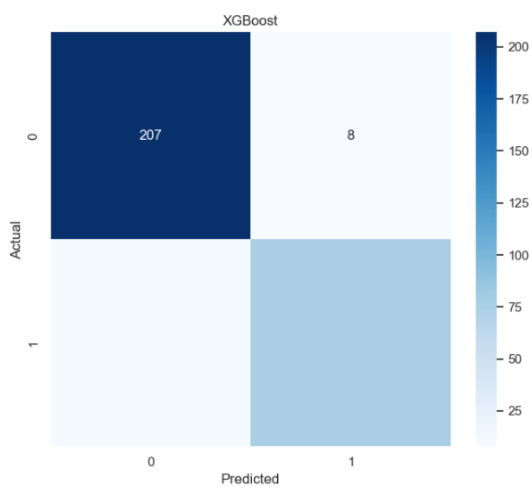

Fig. 11 Confusion Matrix for XGBoost

E. *Hyperparameter Tuning*

TABLE 5. COMPARISON OF SCORE BEFORE AND AFTER HYPERPARAMETER TUNING

Model	Before Tuning	After Tuning (GridSearchCV)	After Tuning (RandomSeachCV)
CatBoost	0.9575	0.9542	0.9542
XGBoost	0.9317	0.9292	0.9292
Random Forest	0.9250	0.9242	0.9225

F. *Feature Importance*

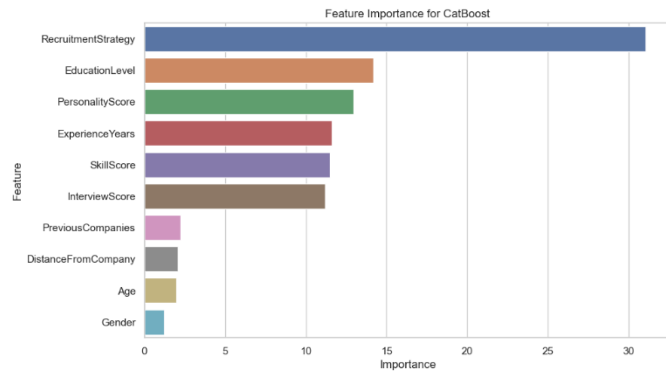

Fig. 12 Feature Importance for CatBoost Model

IV. DISCUSSION

A. *Model Accuracy Scores*

From the chart, it can be observed that CatBoost achieves the highest accuracy score of approximately 0.95, followed closely by Random Forest and XGBoost. Logistic Regression, on the other hand, exhibits the lowest accuracy score among the models compared.

B. *Classification reports for TOP 3 models*

CatBoost is the standout performer among the three models. It demonstrates exceptional accuracy and completeness in identifying both positive and negative instances. This is evident in its excellent precision and recall scores for both classes. The macro and weighted averages are remarkably close, indicating that CatBoost maintains a balanced performance across both classes.

Random Forest also shows strong performance, albeit slightly lower than CatBoost. It excels in precision for class 0, meaning it accurately identifies most positive instances. However, its recall for class 1 is slightly lower, suggesting that it might miss a few positive instances. The weighted average is slightly lower than the macro average, indicating a slight bias towards the majority class.

XGBoost performs similarly to Random Forest. While its precision is comparable, its recall for class 1 is slightly lower than Random Forest. This means it might miss a few more positive instances from class 1. The weighted average is also similar to Random Forest, suggesting a similar bias towards the majority class.

C. ROC-AUC Curves

The ROC-AUC scores extracted from the classification reports align with the relative positions of the curves in the ROC plot. CatBoost, with the highest ROC-AUC score of 0.9292, demonstrates the best overall performance in distinguishing positive and negative instances, as its curve is closest to the top-left corner. Random Forest closely follows, exhibiting slightly better performance than CatBoost with an ROC-AUC score of 0.9309. AdaBoost lags behind, positioned below CatBoost and Random Forest with an ROC-AUC score of 0.9233. The remaining models, Extra Trees, Gradient Boosting, SVM, XGBoost, and LightGBM, display comparable performance, with ROC-AUC scores ranging from 0.9145 to 0.93.

D. Confusion Matrix

Among the three models, CatBoost demonstrated exceptional performance, achieving perfect classification with no misclassifications. Random Forest exhibited moderate performance, correctly classifying most instances but with some errors, primarily in predicting class 1 instances as class 0. XGBoost, on the other hand, had a higher rate of misclassifications, particularly for class 1. Overall, CatBoost's superior performance suggests its effectiveness in handling the given dataset and problem, while Random Forest's ability to correctly classify most instances indicates its potential for practical use. XGBoost’s higher error rate might be attributed to its sensitivity to noise or the specific characteristics of the data.

E. Hyperparameter Tuning

The results indicate that while tuning improved the performance of XGBoost and Random Forest, it had a minimal impact on CatBoost. CatBoost consistently outperformed the other models, even before tuning. This suggests that CatBoost is relatively robust and less sensitive to hyperparameter settings in this particular context. Overall, the tuning process led to slight improvements in the performance of XGBoost and Random Forest, but the differences were not substantial.

F. Feature Importance

In the CatBoost model, RecruitmentStrategy emerges as the most influential feature by a significant margin, indicating that the strategy used in recruiting candidates plays a critical role in the model’s predictions. This feature likely encompasses key details of the hiring process, such as recruitment channels or methodologies, which strongly influence the model’s ability to predict successful candidates. Additionally, EducationLevel and PersonalityScore follow as important factors, emphasizing that a candidate’s formal education and personal traits, like adaptability or interpersonal skills, are heavily considered in hiring decisions. ExperienceYears, SkillScore, and InterviewScore contribute moderately to the model's decisions, suggesting that while professional experience and specific interview performance are relevant, they are less critical compared to the top-ranked factors.

In the RandomForest model, RecruitmentStrategy continues to dominate as the most influential factor, similar to what is observed in the CatBoost and XGBoost models. However, unlike the other models, PersonalityScore and SkillScore rank as the second and third most important features, respectively. This suggests that the RandomForest model places a higher emphasis on personal attributes and skillsets compared to CatBoost and XGBoost. InterviewScore and ExperienceYears appear next in the order of importance, suggesting that while interview performance and professional experience are relevant, they are considered secondary factors. Interestingly, EducationLevel, which ranked higher in the other models, is the least important in the RandomForest model. This could imply that, in this model, practical assessments and interpersonal qualities are valued more than academic qualifications.

In the XGBoost model, RecruitmentStrategy once again stands out as the most important feature, though its dominance is slightly less pronounced than in CatBoost. This suggests that the strategy behind recruitment remains a decisive factor in predicting successful candidates, possibly due to the inherent differences in how candidates are sourced or screened through different strategies. Other key factors include EducationLevel and ExperienceYears, reflecting that the candidate’s educational background and accumulated work experience significantly impact the hiring decisions. InterviewScore also ranks higher in this model compared to CatBoost, indicating that performance in interviews is considered more important for predictions in XGBoost.

G. Challenges Faced

- High Accuracy Scores

When models like CatBoost, Random Forest, and XGBoost all show high accuracy (e.g., around 95%), it becomes difficult to distinguish which model is truly the best. To address this, it’s important to look beyond accuracy and consider other metrics such as precision, recall, F1-score, and especially the ROC-AUC score, which provides a more nuanced view of model performance, particularly in imbalanced datasets. If the ROC-AUC scores are also very close, indicating that all models are similarly good at distinguishing between the classes, examining the ROC curves in detail can help. This involves looking for areas where one model might perform slightly better than others, especially in regions that matter most for your application, such as high sensitivity or specificity.

- Hyperparameter Tuning for a Machine Learning Model

Finding the optimal hyperparameters for a machine learning model can be challenging and time-consuming.

Hyperparameters significantly impact the performance of the model, but manually tuning them is impractical, especially for complex models with many hyperparameters. To address this, automated hyperparameter tuning methods such as GridSearchCV and RandomSearchCV can be used to efficiently search for the best hyperparameters.

H. Real World Implications

- Streamlined Recruitment

Organizations can leverage the machine learning model to automate and optimize their hiring processes, significantly reducing the time and costs associated with recruitment. By automating repetitive tasks such as screening resumes and shortlisting candidates, the model allows HR professionals to focus on more strategic activities. This automation not only speeds up the hiring process but also ensures that no potential candidate is overlooked due to human error or bias. Additionally, the model can analyze large volumes of data quickly and accurately, providing insights that would be time-consuming and difficult to obtain manually. As a result, organizations can achieve more efficient hiring practices, leading to better allocation of HR resources and ultimately improving overall productivity.

- Bias Reduction

The machine learning model can play a crucial role in making more equitable hiring decisions by minimizing human biases. Traditional hiring processes are often influenced by unconscious biases related to gender, age, ethnicity, and other factors, which can lead to unfair hiring practices. By using a data-driven approach, the model evaluates candidates based on objective criteria, such as skills, experience, and qualifications, rather than subjective judgments. This helps promote diversity and inclusion within the organization, as decisions are made based on merit rather than personal biases. A more diverse workforce can bring a variety of perspectives and ideas, leading to a more innovative and balanced workplace.

- Enhanced Decision-Making

HR professionals can leverage the insights provided by the machine learning model to make more informed hiring decisions. By understanding the key factors that contribute to successful hires, such as specific skills, educational background, and work experience, organizations can refine their recruitment strategies to target candidates who are more likely to succeed in their roles. The model can also identify patterns and trends in the data, providing valuable feedback on the effectiveness of different recruitment strategies. This data-driven approach enables HR professionals to make evidence-based decisions, reducing the risk of poor hires and improving overall hiring outcomes. Ultimately, this leads to a more effective and strategic recruitment process, aligning with the organization's goals and needs.

V. CONCLUSION

In conclusion, the study identified CatBoost as the top-performing model with an accuracy of 95%, demonstrating balanced performance across both classes with high precision and recall scores. Random Forest and XGBoost also performed well but exhibited slight biases towards the majority class. The analysis highlighted Recruitment Strategy as the most influential feature across all models, underscoring its critical role in predicting hiring outcomes. Education Level and Personality Score were also significant, emphasizing the importance of formal education and personal traits in hiring decisions. Experience Years and Skill Score contributed moderately, suggesting their relevance but lesser importance compared to the top-ranked factors. Hyperparameter tuning had minimal impact on CatBoost but slightly improved the performance of XGBoost and Random Forest, indicating CatBoost’s robustness and lower sensitivity to hyperparameter settings in this context. These findings suggest that leveraging machine learning models, particularly CatBoost, can significantly enhance recruitment processes by automating and optimizing hiring decisions, reducing biases, and improving overall hiring outcomes.

VI. AREAS FOR FUTURE RESEARCH OR IMPROVEMENTS

- Model Enhancement

Explore additional machine learning algorithms and ensemble methods to further improve prediction accuracy and robustness. Investigating the integration of deep learning techniques could help handle more complex and unstructured data, potentially leading to better performance and new insights.

- Feature Engineering

Develop new features that capture more nuanced aspects of candidate profiles, such as social media activity or psychometric assessments. This could provide a more comprehensive view of candidates and improve the model’s predictive power. Additionally, exploring the impact of different recruitment channels and methodologies on hiring outcomes could yield valuable insights.

- Bias Mitigation:

Conduct in-depth studies on the model’s potential biases and develop techniques to mitigate any identified biases. Implementing fairness-aware machine learning techniques can ensure equitable treatment of all candidates, promoting diversity and inclusion within organizations.

- Scalability and Adaptability:

Investigate the scalability of the model for large-scale recruitment processes across different industries and regions. Adapting the model to cater to specific organizational needs and recruitment practices can enhance its applicability and effectiveness in various contexts.

VII. References

Rąb-Kettler, K., & Lehnervp, B. (Year). *Recruitment in the Times of Machine Learning*. This paper discusses the impact of socio-economic changes and technological advancements on human resources management, emphasizing humanistic management and AI's role in recruitment.

Peña, A., et al. (Year). *Human-Centric Multimodal Machine Learning: Recent Advances and Testbed on AI-Based Recruitment*. This study investigates biases in AI-driven recruitment and proposes methods to ensure fairness, using frameworks such as FairCVtest for bias mitigation.

Chen, T., & Guestrin, C. (2016). *XGBoost: A scalable tree boosting system*. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785-794).

.

Friedman, J. H. (2001). *Greedy function approximation: A gradient boosting machine*. *Annals of Statistics*, 29(5), 1189-1232

Suresh, H., & Guttag, J. V. (2021). A framework for understanding unintended consequences of machine learning. Communications of the ACM, 64(11), 62-71