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Research Paper

Deep Bidirectional Temporal Modeling with Boosted Rule Optimization for Dynamic Ride Demand Forecasting in Smart Cities

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ABSTRACT

Driver attrition has become a major challenge for ride-hailing and transportation-based organizations, as it directly impacts operational performance, workforce stability, and customer satisfaction. Early prediction of employee attrition enables organizations to implement proactive retention strategies and reduce workforce turnover. Traditional attrition prediction methods mainly relied on statistical analysis, manual evaluation, and conventional machine learning techniques, which often struggled to capture hidden relationships and complex feature interactions within high-dimensional employee datasets. To address these limitations, the proposed system introduces a hybrid deep learning and ensemble learning framework for intelligent driver attrition prediction. The proposed BiLSTM-BRC model utilizes a Bidirectional Long Short-Term Memory (BiLSTM) network to perform advanced feature extraction from structured employee data by learning forward and backward feature dependencies. The extracted deep features are then processed using a Boosted Random Committee (BRC) ensemble classifier consisting of Random Forest (RF), Gradient Boosting (GB), and Decision Tree (DT) classifiers combined through a voting mechanism for robust classification. In addition to the extension model, several comparative machine learning algorithms including Random Forest Classifier, Gradient Boosting Classifier, Support Vector Classifier (SVC), and the Greedy LSTM Tree model are also implemented and evaluated for performance analysis. Experimental results demonstrate that the proposed BiLSTM-BRC extension model achieves superior classification performance with approximately 99% prediction accuracy, outperforming existing baseline and hybrid models on the employee attrition dataset. The complete system is implemented using the Flask web framework with integrated modules for user authentication, model training, prediction analysis, and performance visualization, providing an interactive and efficient web-based HR analytics platform.

Keywords: Driver Attrition Prediction, Employee Attrition, Bidirectional Long Short-Term Memory (BiLSTM), Boosted Random Committee (BRC), Ensemble Learning, Deep Learning, Human Resource Analytics, Machine Learning, Flask Framework.

1. INTRODUCTION

Driver attrition refers to the normal process in which drivers leave an organization due to various reasons, such as resignation, dissatisfaction, retirement, or better employment opportunities. Several factors can contribute to driver attrition. Driver attrition occurs when drivers leave the organization at a faster rate than new drivers are hired, as shown in Fig. 1.1. When drivers leave the organization, the resulting vacancies often remain unfilled for a period of time, causing operational difficulties and financial losses for the organization. The driver attrition rate is an important indicator used to evaluate the stability and progress of an organization. A high attrition rate indicates that drivers are leaving the organization frequently. High attrition can lead to the loss of organizational productivity, increased recruitment and training costs, and reduced overall efficiency. Therefore, in order to ensure the continuous growth and smooth functioning of the organization, it is essential to control and reduce the driver attrition rate.

Many types of driver attrition help us to understand the attrition process. The attrition type is whether drivers choose to leave the company voluntarily. The involuntary attrition type is when the organization ends the employment process. The external attrition type is referred to when Driver leaves an organization to work for another organization. Internal attrition occurs when Driver is given another position within the same organization as a promotion. The driver attrition rate is the measure of people who leaves the organization. By measuring the attrition rate, we can identify the causes and factors that need to be solved to eliminate driver attrition. The attrition rate is calculated by dividing the number of Driver who have left the company by the average number of drivers over some time. The attrition rate helps us find the company's progress over a specific period.

The Driver attrition states demonstrate that after six months of job duration, 1/3 of new Drivers leave the organization. The 3 to 4.5 million drivers leave their job every month in the United States, according to the Job Openings and Labor Turnover Survey (JOLTS). The driver attrition rate is 57.3% in 2021 to the report of the Bureau of Labor Statistics. The report also suggests that in many industries, the driver attrition rate is close to 19%. The cost per hire of a new Driver is USD 4129 by SHRM. Ninety percent of drivers retention rate is considered suitable for a company, and the attrition rate must be less than 10%.

2. Related Work

The rapid growth of ride-hailing platforms (RHPs) has transformed urban mobility by providing flexible transportation services through digital platforms. With increasing market penetration, researchers have explored various aspects of RHP operations, including regulatory policies, pricing mechanisms, platform competition, driver behavior, sustainability, and operational optimization. Existing studies primarily focus on mathematical modeling and empirical analysis to improve platform efficiency and market performance.

2.1 Regulatory Policies and Platform Competition

Regulatory policies and market competition play a crucial role in shaping ride-hailing platform operations. Sun et al. [1] investigated the influence of regulatory policies on RHP operations and examined how policy frameworks affect platform growth. Similarly, Xi et al. [2] developed a multi-leader–multi-follower model to analyze competition among platforms and optimize operational strategies. Cohen and Zhang [4] further contributed by developing an endogenous model for two-sided RHP markets, enabling analytical determination of optimal service pricing and commission rates. Zhong et al. [5] extended this perspective by examining competition between RHPs and traditional taxi services, proposing pricing strategies suitable for both regulated and unregulated environments. These studies collectively highlight the importance of regulatory frameworks and competitive dynamics in determining platform sustainability and profitability.

2.2 Pricing Strategies and Commission Optimization

Pricing and commission policies have emerged as central factors influencing ride-hailing platform efficiency. Deng et al. [8] explored the impact of commission rates on drivers' switching behavior within dynamic mobility markets. Using queue-theory-based mathematical models, the study examined the relationship between commission structures, driver behavior, and platform performance under duopoly and competitive market conditions. Ke and Qian [11] proposed an optimal pricing scheme designed to improve platform operations, while Yao and Zhang [12] employed a many-to-many matching framework to address pricing problems in multi-modal transportation networks. Furthermore, Sun and Ertz [14] utilized system dynamics modeling to identify commission rates, order prices, and investment levels as key variables influencing operational performance. These findings indicate that pricing and commission mechanisms remain fundamental tools for balancing profitability and service efficiency.

2.3 Operational Models and Driver Behavior

The operational efficiency of ride-hailing systems depends heavily on driver participation and behavioral dynamics. Bandiera et al. [3] developed a mathematical model to simulate interactions between service providers and customers, contributing to a better understanding of platform operational behavior. Xu et al. [15] empirically analyzed drivers' responses to ride-hailing requests and demonstrated that economic incentives significantly influence driver acceptance behavior. Deng et al. [8] similarly examined drivers' switching decisions across competing platforms, emphasizing the role of financial considerations in mobility markets.

Despite these advancements, certain limitations remain in existing operational models. Previous studies often simplify driver behavior by assuming stable driver populations and neglecting long-term variations in workforce participation [7]. Such assumptions limit the applicability of these models in highly dynamic mobility environments, where fluctuations in driver availability may significantly affect platform performance and commission optimization.

2.4 Sustainability and Safety Considerations

Recent research has increasingly emphasized sustainability and driver welfare within ride-hailing ecosystems. Lyu et al. [6] explored electric ride-hailing vehicles (ERVs) as an emerging mobility paradigm, highlighting their environmental benefits and intelligent scheduling capabilities. Compared with conventional fuel-powered ride-hailing vehicles, pure electric vehicles were shown to substantially reduce carbon emissions during operation. Alongside environmental concerns, driver health and operational safety have gained research attention. Chen et al. [10] investigated smoking behavior among Chinese ride-hailing drivers and linked it to occupational stress within the industry. Additionally, Chen et al. [13] examined the impact of distractions in ride-hailing systems on taxi drivers' performance and safety, identifying distraction-related risks that may negatively affect driving behavior and operational reliability.

2.5 Order Assignment and Platform Efficiency

Order allocation strategies represent another important area of ride-hailing research. Sun et al. [9] investigated different order assignment mechanisms and found that distinct assignment strategies exert varying effects on platform efficiency and operational outcomes. Efficient order matching not only improves customer satisfaction but also influences driver utilization and overall platform productivity.

2.6 Research Gap

Although substantial research has addressed pricing strategies, regulatory policies, driver behavior, and operational optimization in ride-hailing platforms, existing studies predominantly focus on isolated operational factors. Most models rely on simplified assumptions regarding driver behavior and stable market conditions, limiting their ability to capture real-world mobility dynamics. Furthermore, limited attention has been given to integrated frameworks that simultaneously consider regulatory influence, dynamic driver participation, sustainable mobility, and operational efficiency. Therefore, there remains a need for comprehensive and adaptive models capable of addressing the interconnected challenges faced by modern ride-hailing platforms.

3. PROPOSED METHODOLOGY

The proposed system introduces an intelligent, automated, and data-driven approach for predicting attrition risk using Machine Learning techniques and a web-based deployment framework as demonstrated in Fig. 1. The system replaces manual analysis with a structured pipeline that processes real-time data, learns hidden behavioral patterns, and provides accurate attrition predictions through an interactive user interface.

Data Collection

Structured employee attrition datasets are collected containing employee-related attributes such as demographic information, work conditions, job satisfaction levels, relationship satisfaction, environmental satisfaction, work-life balance, and performance indicators. The dataset includes attributes such as Age, Department, Job Role, Monthly Income, Gender, Marital Status, Environment Satisfaction, Job Satisfaction, Performance Rating, Relationship Satisfaction, and WorkLife Balance. These attributes are used as input features for training and evaluating the machine learning and deep learning models developed for employee attrition prediction.

Data Preprocessing

The collected dataset undergoes multiple preprocessing operations to improve data quality and prepare it for model training. Initially, unnecessary attributes such as EmployeeCount, EmployeeNumber, Over18, and StandardHours are removed from the dataset. Categorical attributes are converted into numerical format using Label Encoding techniques. Feature scaling and normalization are performed using StandardScaler to maintain consistent data distribution across all features. Target variables are also transformed into machine-readable numerical labels for effective classification. These preprocessing techniques improve model efficiency and prediction performance.

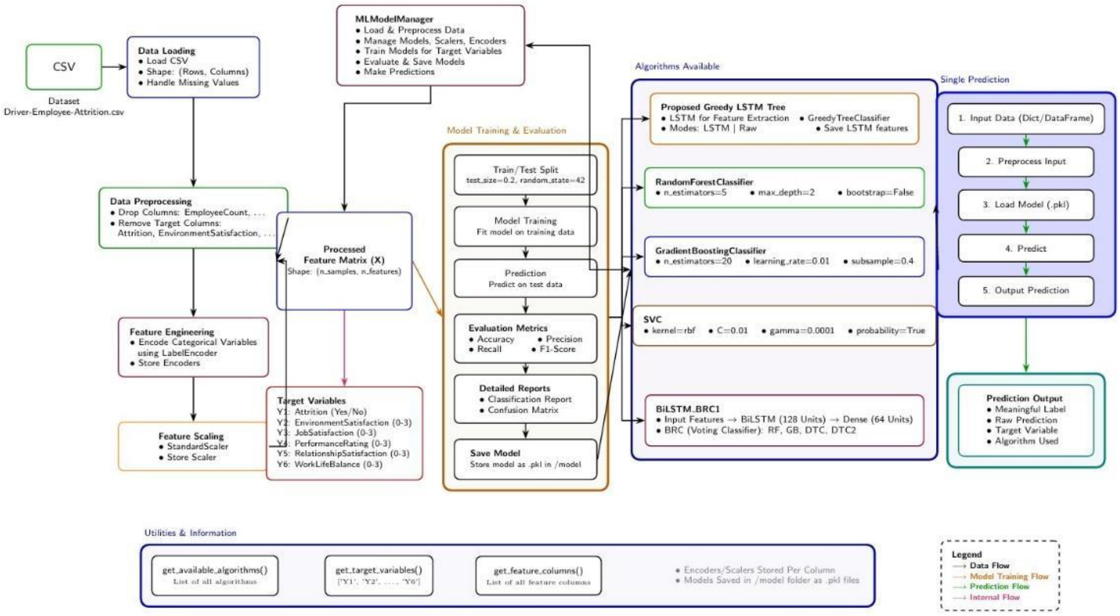


Fig. 1: Proposed system architecture.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis is performed to understand the distribution and relationships among the dataset attributes. Statistical analysis and visualization methods are used to analyze employee distributions, department-wise attrition, satisfaction-level variations, gender distribution, marital status, and correlation among numerical features. Correlation matrices and satisfaction score distributions help identify the most influential factors affecting employee attrition and organizational stability.

Feature Selection

Feature selection is carried out to identify the most significant attributes contributing to employee attrition prediction. Important features are selected based on statistical importance, feature correlation, and domain relevance. Redundant and weakly contributing attributes are eliminated to reduce computational complexity and improve model generalization and prediction accuracy.

Model Training

Multiple ML and DL algorithms are trained using the processed dataset for comparative performance analysis. The implemented algorithms include RF, GB, SVC, Proposed GLSTMT, and the extension hybrid model BiLSTM-BRC. The GLSTMT model combines LSTM-based feature extraction with a GT classifier for prediction. The extension BiLSTM-BRC model utilizes BiLSTM for deep feature extraction and a BRC ensemble consisting of RF, GB, and DT classifiers for final classification.

Model Evaluation

The trained models are evaluated using standard classification performance metrics such as Accuracy, Precision, Recall, F1-Score, Classification Report, and Confusion Matrix. These metrics are used to measure the effectiveness of the models in predicting employee attrition and satisfaction-related outcomes. Experimental analysis demonstrates that the proposed hybrid models achieve superior prediction performance compared to conventional machine learning techniques.

Model Integration

After training and evaluation, the best-performing models are serialized and stored using Joblib for future reuse and deployment. The trained models are integrated with the backend application logic, allowing the system to dynamically process employee input data and generate prediction results in real time.

Web Application Deployment

A secure and interactive web-based HR analytics application is developed using the Flask framework. The application provides separate modules for user authentication, HR management, model training, prediction analysis, and performance visualization. The system enables HR managers and authorized users to input employee details, perform model-based attrition prediction, and visualize classification performance through an intuitive graphical interface.

Result Interpretation and Decision Support

The prediction system analyzes employee attrition risk and categorizes employees based on predicted outcomes. The generated insights assist HR managers in identifying employees with high attrition risk and support proactive decision-making strategies for employee retention, workforce planning, and organizational performance improvement. The system helps organizations reduce employee turnover and improve operational efficiency through data-driven HR analytics.

BiLSTM

BiLSTM (Bidirectional Long Short-Term Memory) is an advanced DL architecture designed to learn sequential patterns by processing input data in both forward and backward directions. Unlike traditional LSTM models that analyze information only from past to future, BiLSTM captures dependencies from both previous and future contexts, enabling improved feature learning and prediction accuracy. In this project, BiLSTM is used for deep feature extraction from employee attrition data. The model learns hidden relationships among employee attributes such as job satisfaction, work-life balance, environment satisfaction, and performance ratings. These extracted features are then utilized by the BRC ensemble classifier for final attrition prediction.

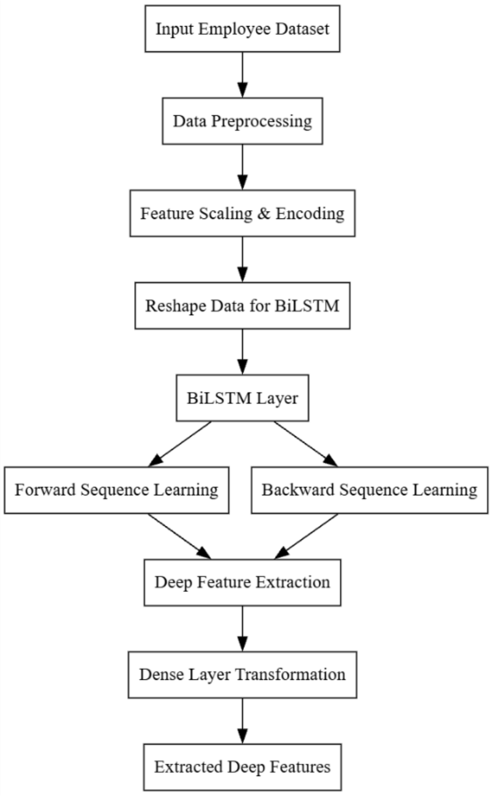


Fig. 2: Internal working of BiLSTM model.

Step 1: Input Data Preparation

The preprocessed employee dataset is first converted into a numerical format suitable for DL processing. Feature scaling and normalization are performed to maintain consistent data distribution across all attributes. The input data is then reshaped into a three-dimensional structure required by the BiLSTM network.

Step 2: Bidirectional Sequence Processing

The BiLSTM layer processes the input sequence in both forward and backward directions simultaneously. This dual-direction learning enables the model to capture hidden dependencies and relationships among employee attributes more effectively than standard LSTM models.

Step 3: Feature Extraction

After sequence processing, the BiLSTM layer generates high-level latent feature representations from the input data. These extracted features contain meaningful information related to employee behavior, satisfaction levels, and attrition patterns, improving classification capability.

Step 4: Dense Layer Transformation

The extracted features are passed through dense neural network layers with activation functions such as ReLU. These dense layers further refine and transform the learned features into a more compact and informative representation suitable for classification.

Step 5: Ensemble-Based Classification

The transformed features generated by the BiLSTM model are provided as input to the BRC ensemble classifier. The ensemble combines multiple ML algorithms such as RF, GB, and DT to perform final employee attrition prediction with improved robustness and prediction performance.

Step 6: Prediction Output Generation

The trained BiLSTM-BRC model generates the final prediction results by classifying employees into attrition-related categories. The system evaluates the prediction outcomes using performance metrics such as accuracy, precision, recall, and F1-score.

BRC Model

BRC is an ensemble-based ML classification approach that combines the prediction capabilities of multiple classifiers to improve overall model performance and prediction stability. Instead of depending on a single classifier, BRC integrates multiple ML algorithms such as RF, GB, and DT to generate more reliable and accurate prediction results. In this project, BRC is used as the final classification component of the BiLSTM-BRC hybrid model. The deep features extracted by the BiLSTM network are provided to the BRC ensemble classifier, which performs employee attrition prediction using collective decision-making through ensemble voting techniques.

Step 1: Feature Input Collection

The deep features extracted from the BiLSTM network are collected and prepared as input for the BRC classifier. These features contain important hidden patterns and employee behavior information learned during deep feature extraction.

Step 2: Initialization of Multiple Classifiers

The BRC model initializes multiple ML classifiers including RF, GB, and DT. Each classifier independently learns different decision boundaries and feature relationships from the extracted feature dataset.

Step 3: Individual Model Training

Each classifier within the BRC ensemble is trained separately using the BiLSTM-generated feature representations. During training, the models learn employee attrition patterns and develop their own prediction strategies based on the input data.

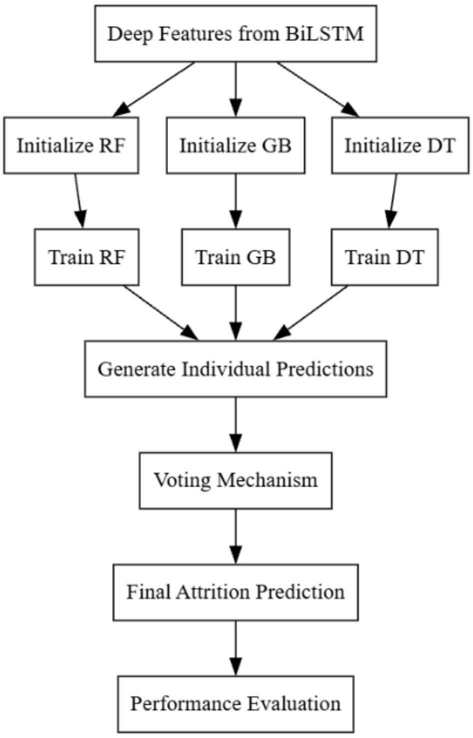


Fig. 3: Internal working of BRC model.

Step 4: Ensemble Voting Mechanism

After training, all classifiers generate their individual predictions for the input data. The BRC model combines these outputs using a voting mechanism to determine the final prediction result based on the collective decision of all classifiers.

Step 5: Final Prediction Generation

The ensemble voting result is considered as the final attrition prediction output. This collaborative decision-making process improves classification reliability and reduces the probability of incorrect predictions from individual models.

Step 6: Performance Evaluation

The final prediction results generated by the BRC model are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The ensemble approach generally provides improved prediction performance compared to single-model classifiers.

4. Result Description

Fig. 4 presents the performance results and classification reports generated by the proposed GLSTMT model for multiple target attributes related to driver attrition analysis.

Fig. 4 (a) The Attrition classification report illustrates the model's capability to accurately distinguish between drivers who remain in the organization and those who leave. The evaluation metrics such as precision, recall, and F1-score demonstrate the strong classification performance of the proposed model in attrition prediction.

Fig. 4 (b) The Environment Satisfaction analysis evaluates the effectiveness of the proposed model in classifying satisfaction levels associated with the driver work environment. The classification report indicates accurate identification of satisfaction categories ranging from low to very high.

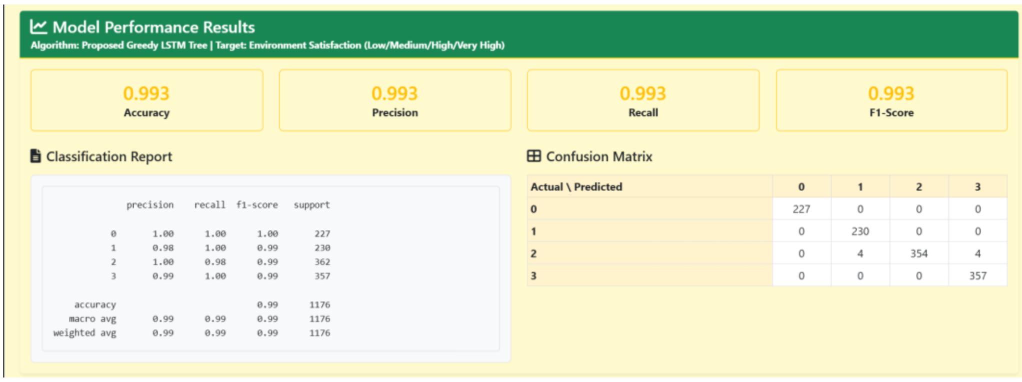
Fig. 4 (c) The Job Satisfaction report demonstrates the model's capability to classify driver satisfaction levels related to job roles, responsibilities, and engagement within the organization. The evaluation metrics reflect the strong predictive performance of the proposed hybrid model.

Fig. 4 (d) The Performance Rating report evaluates the classification accuracy of the GLSTMT model in predicting driver performance categories. The results demonstrate precise identification of performance levels based on historical driver attributes.

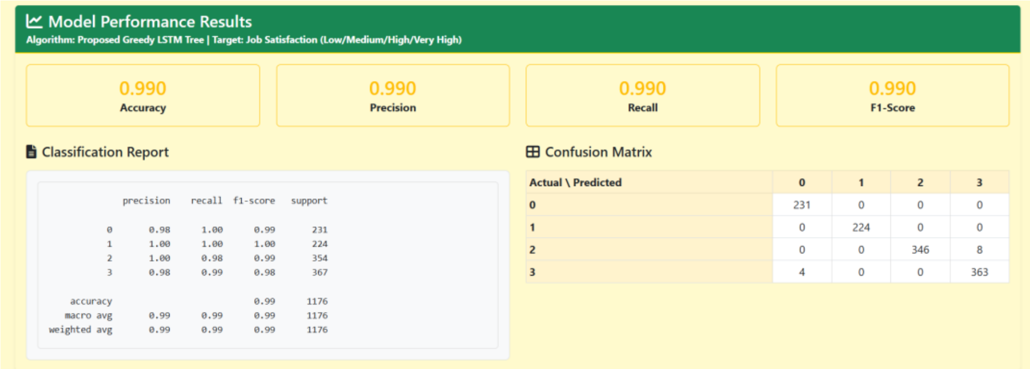
Fig. 4 (e) The Relationship Satisfaction report reflects the model's ability to classify variations in satisfaction related to relationships between drivers and management. The classification metrics highlight accurate identification of interpersonal satisfaction levels.

Fig. 4 (f) The Work Life Balance report measures the model's capability to classify drivers according to their balance between professional responsibilities and personal life. The results demonstrate the strong performance of the proposed model in identifying work-life balance levels within the driver dataset.

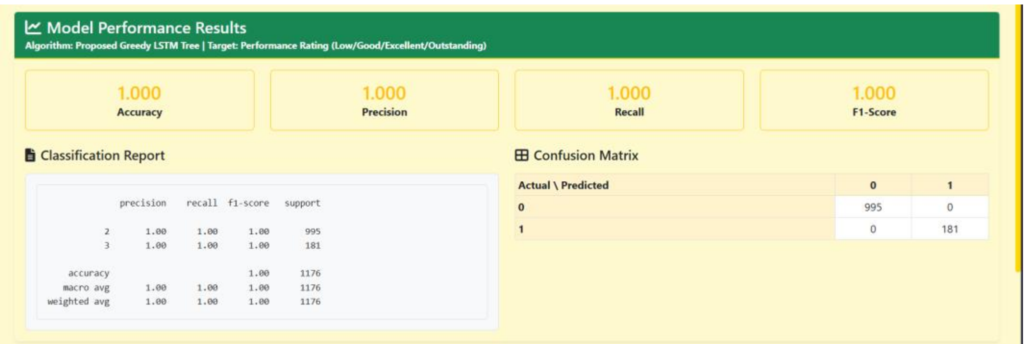
(a)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Environment Satisfaction (Low/Medium/High/Very High)
0.993 Accuracy
0.993 Precision
0.993 Recall
0.993 F1-Score
Classification Report
precision recall f1-score support
0 1.00 1.00 1.00 227
1 0.98 1.00 0.99 230
2 1.00 0.98 0.99 362
3 0.99 1.00 0.99 357
accuracy 0.99 1176
macro avg 0.99 0.99 0.99 1176
weighted avg 0.99 0.99 0.99 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 227 0 0 0
1 0 230 0 0
2 0 4 354 4
3 0 0 0 357

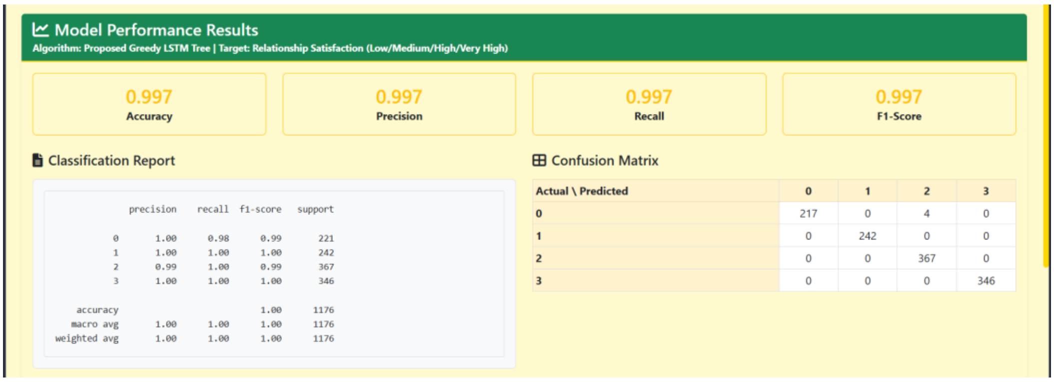
(b)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Job Satisfaction (Low/Medium/High/Very High)
0.990 Accuracy
0.990 Precision
0.990 Recall
0.990 F1-Score
Classification Report
precision recall f1-score support
0 0.98 1.00 0.99 231
1 1.00 1.00 1.00 224
2 1.00 0.98 0.99 354
3 0.98 0.99 0.98 367
accuracy 0.99 1176
macro avg 0.99 0.99 0.99 1176
weighted avg 0.99 0.99 0.99 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 231 0 0 0
1 0 224 0 0
2 0 0 346 8
3 4 0 0 363

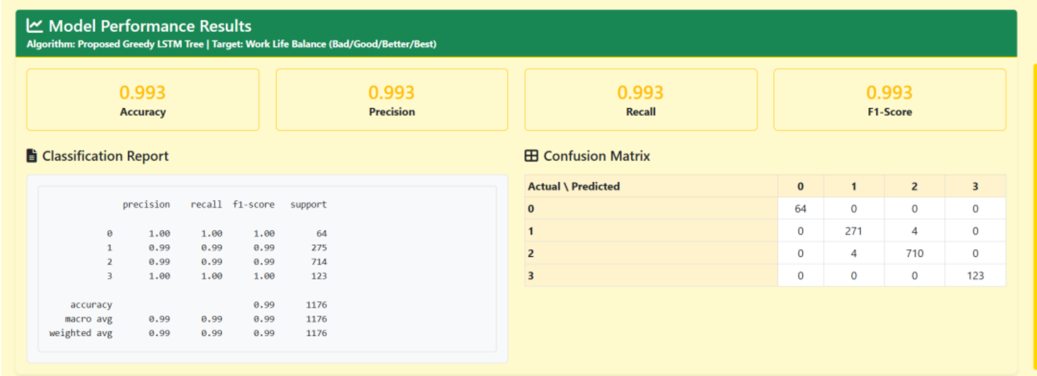
(c)


Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Performance Rating (Low/Good/Excellent/Outstanding)
1.000 Accuracy
1.000 Precision
1.000 Recall
1.000 F1-Score
Classification Report
precision recall f1-score support
2 1.00 1.00 1.00 995
3 1.00 1.00 1.00 181
accuracy 1.00 1176
macro avg 1.00 1.00 1.00 1176
weighted avg 1.00 1.00 1.00 1176
Confusion Matrix
Actual \ Predicted 0 1
0 995 0
1 0 181

(d)

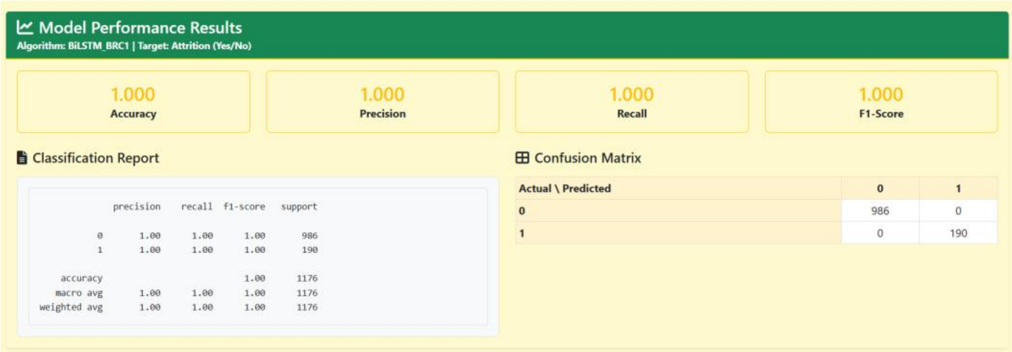

Model Performance Results
Algorithm: Proposed Greedy LSTM Tree | Target: Relationship Satisfaction (Low/Medium/High/Very High)
0.997 Accuracy
0.997 Precision
0.997 Recall
0.997 F1-Score
Classification Report
precision recall f1-score support
0 1.00 0.98 0.99 221
1 1.00 1.00 1.00 242
2 0.99 1.00 0.99 367
3 1.00 1.00 1.00 346
accuracy 1.00 1176
macro avg 1.00 1.00 1.00 1176
weighted avg 1.00 1.00 1.00 1176
Confusion Matrix
Actual \ Predicted 0 1 2 3
0 217 0 4 0
1 0 242 0 0
2 0 0 367 0
3 0 0 0 346

(e)

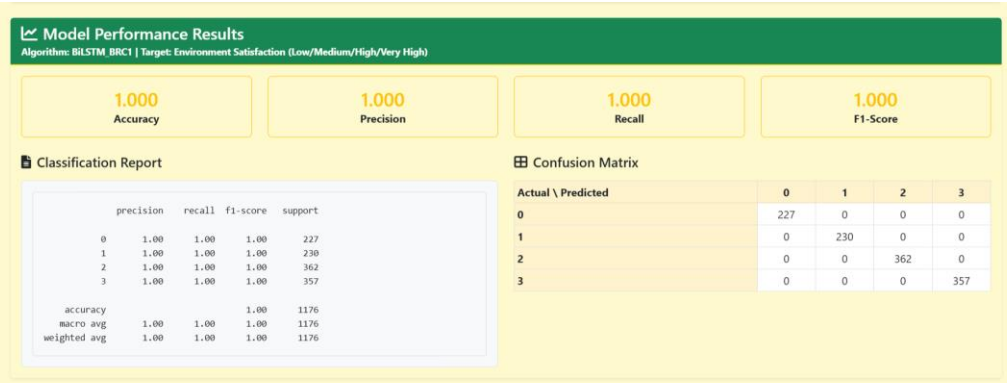


(f)

Fig. 4: Performance and classification reports of various target attributes from GLSTMT Model (a) Attrition, (b) Environment Satisfaction, (c) Job Satisfaction, (d) Performance Rating, (e) Relationship Satisfaction, (f) Work Life Balance.



(a)



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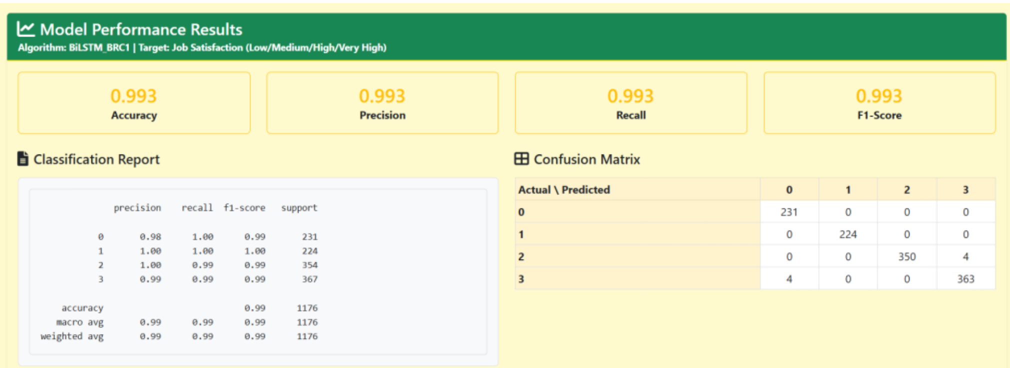

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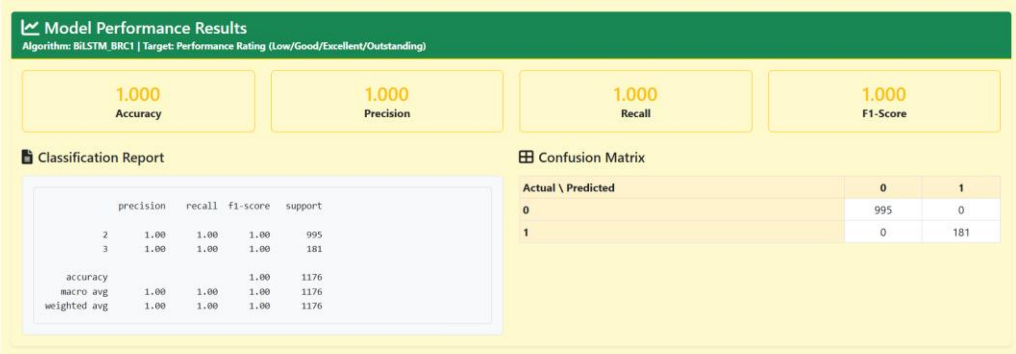
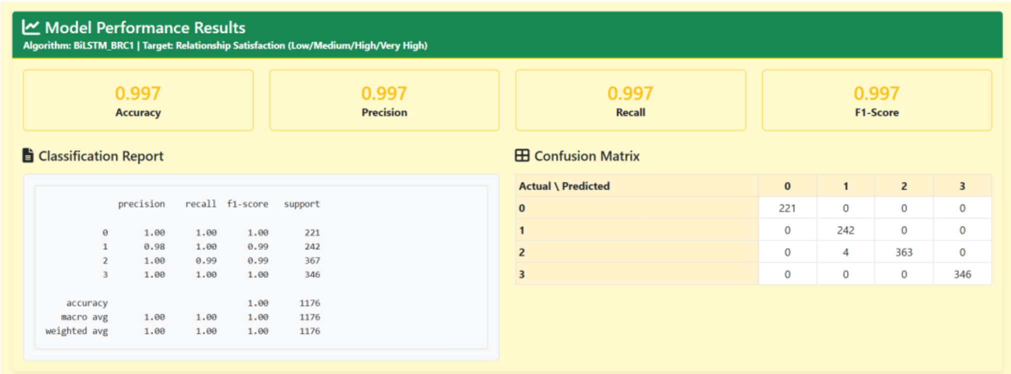
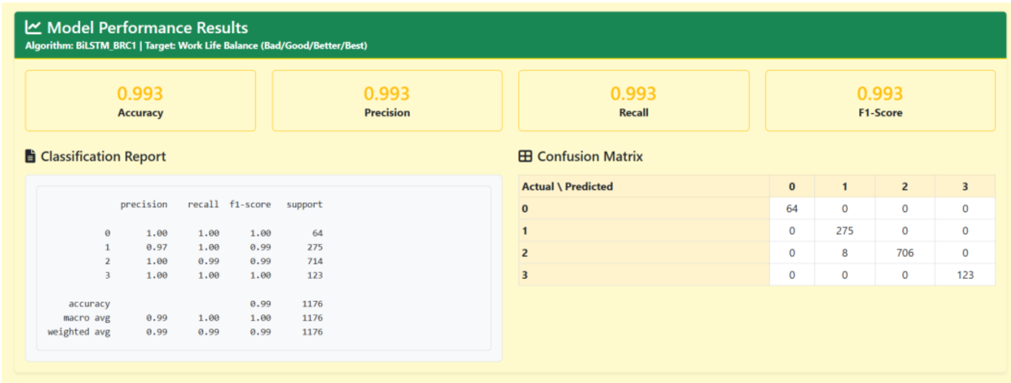


(d)



(e)



(f)

Fig. 5: Performance and classification reports of various target attributes from BiLSTM-BRC Model (a) Attrition, (b) Environment Satisfaction, (c) Job Satisfaction, (d) Performance Rating, (e) Relationship Satisfaction, (f) Work Life Balance.

Fig. 5 presents the performance results and classification reports generated by the BiLSTM-BRC model for multiple target attributes related to driver attrition analysis.

Fig. 5 (a) The Attrition classification report illustrates the model's capability to accurately distinguish between drivers who remain in the organization and those who leave. The evaluation metrics such as precision, recall, and F1-score demonstrate the strong classification performance of the BiLSTM-BRC model in attrition prediction.

Fig. 5 (b) The Environment Satisfaction analysis evaluates the effectiveness of the BiLSTM-BRC model in classifying satisfaction levels associated with the driver work environment. The classification report indicates accurate identification of satisfaction categories ranging from low to very high.

Fig. 5 (c) The Job Satisfaction report demonstrates the model's capability to classify driver satisfaction levels related to job roles, responsibilities, and engagement within the organization. The evaluation metrics reflect the strong predictive performance of the hybrid BiLSTM-BRC model.

Fig. 5 (d) The Performance Rating report evaluates the classification accuracy of the BiLSTM-BRC model in predicting driver performance categories. The results demonstrate precise identification of performance levels based on historical driver attributes.

Fig. 5 (e) The Relationship Satisfaction report reflects the model's ability to classify variations in satisfaction related to relationships between drivers and management. The classification metrics highlight accurate identification of interpersonal satisfaction levels.

Fig. 5 (f) The Work Life Balance report measures the model's capability to classify drivers according to their balance between professional responsibilities and personal life. The results demonstrate the strong performance of the BiLSTM-BRC model in identifying work-life balance levels within the driver dataset.

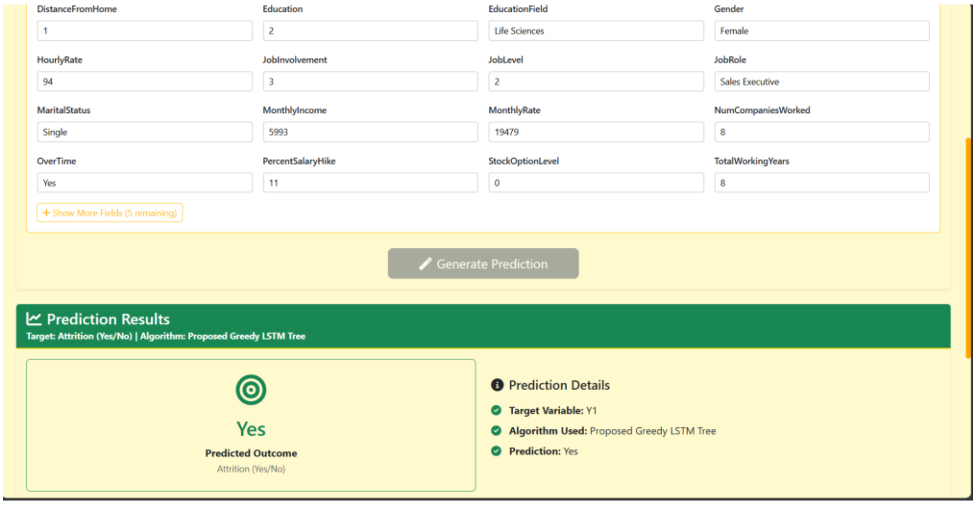


Fig. 6: Predictions on test data.

The prediction screen Fig. 6 presents the attrition results for employees, indicating the probability of leaving. HR managers receive actionable insights to identify high-risk employees and take preventive measures to reduce turnover.

5. Conclusion

This research successfully designed and implemented an intelligent Driver Attrition Prediction System using ML and DL techniques. The system integrated data preprocessing, feature engineering, model training, performance evaluation, and web-based prediction modules within a unified Flask application framework. Multiple algorithms including RF, GB, SVC, Proposed GLSTMT, and the extension hybrid model BiLSTM-BRC were implemented and evaluated for comparative analysis. The proposed GLSTMT model combined LSTM-based deep feature extraction with GT classification, while the extension BiLSTM-BRC model utilized BiLSTM-based feature learning with an ensemble BRC classifier consisting of RF, GB, and DT models. Experimental evaluation demonstrated that the hybrid models achieved superior prediction performance compared to traditional ML algorithms. The system also provided detailed classification analysis using metrics such as accuracy, precision, recall, F1-score, classification reports, and confusion matrices. In addition, the Flask-based web application enabled secure authentication, role-based access control, real-time prediction generation, and interactive HR analytics dashboards for both HR managers and employees. The implemented system effectively identified employees with high attrition risk and supported data-driven workforce management decisions. Overall, the research delivered a scalable, efficient, and intelligent solution for employee attrition prediction and organizational decision support.

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