DETECTION AND PREVENTION OF WORKFLOW ATTRITION

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ABSTRACT:

Any corporation understands the importance of the workforce in attaining and maintaining a competitive advantage. Workflow attrition rates should be recognized as an interfering element in a business's growth. Making decisions can play an important role in administration and may indicate the most vital component in the planning process. Attrition is a well-known issue that necessitates sound management decisions in order to retain highly qualified staff. In order to reduce workflow attrition, organizations today have a strong business interest in understanding the factors that contribute to this occurrence. There are several factors leading to the attrition. Predicting employee attrition and determining the key contributors to attrition are thus important organizational goals in order to optimize their human resource strategy. Excitingly, Artificial Intelligence (AI), Machine Learning, and Deep Learning have been actively used, in forecasting attrition probabilities in advance using an automated technique. The goal of this research is to utilize machine and deep learning models and compare them to bring out the highest possible accuracy. We aspire to use Artificial Neural Networks (ANN) and Convolutional Neural Networks(CNN) Algorithms to reach accuracy up to 94%, compared to the previous high of 92%.

Keywords: Workflow Attrition, Predictive model, Deep Learning and Neural Networks, Dataset enhancement

1. INTRODUCTION

In the intricate landscape of contemporary business operations, workforce attrition stands as a complex phenomenon, encompassing departures through retirement, resignation, and organizational shifts. The repercussions of a high staff attrition rate on organizations are profound, influencing their competitive standing and operational efficiency. As employees depart, they carry with them invaluable tacit information, often serving as a competitive advantage for the company. The ensuing staff turnover disrupts the company's workflow, creating a void in creativity and imposing substantial costs related to hiring, training, and business disruptions.

Conversely, a strategy centered around higher retention not only mitigates these costs but also introduces seasoned employees into the workforce, contributing to organizational stability. The essence of building and sustaining a collaborative workplace lies in attracting and retaining individuals who synergize effectively. Recognizing the pivotal role of human resources (HR), the division becomes instrumental in crafting an atmosphere conducive to collaboration by leveraging employee database records. This, in turn,

empowers management to make informed decisions, ultimately reducing staff turnover.The integration of artificial intelligence (AI) into the realm of human resource management has become a focal point for researchers seeking to address the challenges posed by employee attrition. The utilization of the IBM Watson dataset, comprising 35 characteristics for 1470 samples from current and previous employees, serves as a testing ground for advanced predictive models. The inherent complexity of this dataset, marked by inconsistency, presents a formidable challenge for accurate predictions.
This research endeavors to make significant contributions to the field by enhancing the predictive accuracy of employee attrition. Firstly, a strategic integration of deep learning techniques, coupled with nuanced pre-processing operations, is introduced to elevate the capabilities of the predictive model. Secondly, a meticulous examination of dataset features is conducted, unraveling interrelationships and identifying the most critical aspects influencing attrition.

A notable augmentation to the dataset involves the inclusion of contemporary factors that may impact attrition, such as work mode, feedback mechanisms, recognition practices, the quality of the hiring process, and the influence of workplace culture. This comprehensive approach acknowledges the intricate interconnections within the dataset, aiming to provide a more nuanced understanding of the dynamics contributing to attrition To ensure the practicality and applicability of the results, the model is rigorously tested on both overbalanced and imbalanced datasets. The research recognizes the need for a holistic approach in understanding attrition, considering the intricate web of factors that contribute to workforce dynamics.Proposing advanced techniques for predicting employee attrition, the research explores ensemble models of deep learning, employing methodologies such as Bagging, boosting, and stacking. Within the realm of convolutional neural networks (CNN), the application of 1-D Convolutions is explored. For recurrent neural network (RNN) algorithms, the research investigates Bidirectional RNN and Long-Short Term Memory (LSTM), specifically utilizing the classic cell states and gates.

This methodical exploration of advanced algorithms is designed to overcome challenges associated with data overfitting, providing a robust foundation for accurate attrition predictions.
In conclusion, this comprehensive introduction sets the stage for an in-depth exploration of the complexities surrounding workforce attrition, the transformative potential of artificial intelligence in predictive modeling, and the innovative strategies proposed in this research. The ensuing sections will delve deeper into each facet, unraveling the intricacies and offering insights into a holistic approach towards addressing the challenges posed by employee attrition in contemporary organizational contexts.

2. LITERATURE OVERVIEW

Pradip Kumar Talapatra et al.[1] explored the attrition rate and the perspective of industries in India which have factors of their own. They concluded that benefits not meeting their needs is highest factor of attrition.

Fatemeh Mozaffari et al.[2] analyzed and came to a conclusion that by using the gradient boosting model ML model they could achieve their accuracy rate up to 89%.

Ali Raza et al.[3] utilized the Machine Learning Algorithms like Extra Trees Classifier (ETC), Support vector machine (SVM), Logistic Regression (LR), and Decision Tree Classifier (DTC), compared them in accuracy term and could achieve up to 90%.

Mohammed A. Abu Rumman et al.[4] explored machine learning and deep learning algorithms , he came to the conclusion that all the ML Algorithms like KNN, Random Forests (RF), and SVM using various parameters.

Shobhanam Krishna et al.[5] explored Employee Attrition Analysis using Random Forest and he found out that the model built using Random Forest Classifier is transformed by SMOTE mechanism to improve target class imbalance. After SMOTE mechanism metrics of the training model are improved however, validation metrics are improved slightly specially sensitivity has very little impact.

Karthik Sekaran et al.[6] explored two powerful Explainable AI (XAI) models named Local Interpretable Model-Agnostic Explainer (LIME) and Shapley Additive eXplainer (SHAP) which unveiled logical insights from the data that could assist the management authorities in countermeasure the risk of employee attrition.

Md. Monir Ahammod Bin Atique et al.[7] used the method called CatBoost in which a state-of-the-art boosting method, CatBoost, and a feature engineering process have been applied for detecting and analyzing employee attrition which reveals the best recall rate of 0.89, with an accuracy of .8945.

Sumati Sidharth et al.[8] used Random Forest and the AdaBoost classifier to make predictions. Their paper also introduces the factors that influence employee attrition inside any organization and will provide a clear perspective to top management in making key decisions regarding the retention of most of the workforce in the organization.

Hamamache Kheddouci et al.[9] explains the prediction systems are not generic and are specific to each company and a generic attrition model based on bipartite graph properties and machine learning algorithms is developed.

Sini Raj Pulari et al.[10] analyzes Employee Attrition Using Machine Learning and Deep Learning Techniques where the analysis of data have used deep learning methodologies and machine learning techniques[21-22] to gather more valuable insights than using the traditional methods.

3. METHODOLOGY

3.1 Dataset

The dataset used is the ‘IBM HR Analytics Employee attrition and performance’ retrieved from Kaggle. The number records in it are up to 1450.

Our implied ML and DL models analyze the dataset to identify the most pertinent data points that improveaccuracy and develop a projecting model in accordance with the following steps:

Collecting a database of employee information.

Dataset Enhancement: The dataset initially has 35 features from 1,470 workers. We have enhanced the dataset by adding 4 morecategorical features which are apt features for the present working conditions. We used pandas DataFrame methods to add and enhance the data.

Data Preprocessing: Pre-processing is an important step in machine and deep learning that significantly improves model performance. Pre-processing includes normalizing, cleaning, and categorizing data en-coding.

Preparing the collected Dataset:The dataset has been cleaned and standardized by using scalars. Some of the attributes found in this data set are categorical rather than numerical. Most ML and DL algorithms do not support categorical features right away. The original data includes multiple

Features	Type
Work mode	Categorical
Toxic environment	Categorical
Appreciation	Categorical
Hring process	Categorical

Table 1: Added features and their types

Type categorical variables such as

(BusinessTravel, Departments, Education Field, Gender, Job Role,Marital Status, and Over Time). This type of feature should be associated with numerical numbers. To convert them, "one hot encoding" and “Label Encoding” came into play. missing values are dealt with ML imputation. The most crucial dataset attributes are found for Attrition analysis.

Dividing the dataset: Divide the dataset into train, validate, and test. Train and test the proposed models by

using train and validate data. Using the test data, test

the proposed models.

Fig-1: Table of already existing features and their types

Feature Name	Type	Feature Name	Type
Age	Numeric	Distance From Home	Numeric
Monthly Income	Numeric	Over Time	Categorical
Business Travel	Categorical	Education	Categorical
Monthly Rate	Numeric	Percent Salary Hike	Numeric
Daily Rate	Numeric	Education Field	Categorical
Number of Companies Worked	Numeric	Performance Rating	Numeric
Department	Categorical	Relationship Satisfaction	Categorical
Over 18	Categorical	Employee Number	Numeric
Employee Count	Numeric	Standard Hours	Numeric
Environment Satisfaction	Categorical	Stock Option Level	Categorical
Gender	Categorical	Training Times Last Year	Numeric
Total Working Years	Numeric	Job Involvement	Categorical
Hourly Rate	Numeric	Work Life Balance	Categorical
Job Level	Categorical	Years Since Last Promotion	Numeric
Years At Company	Numeric	Job Satisfaction	Categorical
Job Role	Categorical	Years With Current Manager	Numeric
Years In Current Role	Numeric	Marital Status	Categorical
Attrition	Categorical		

3.2 Data Analysis and Visualization

The data in the dataset, is analyzed before putting into the models by using the EDA method. EDA is the process of analyzing and visualizing data to obtain insights, uncover patterns, and comprehend the features of a dataset.To prepare the dataset for modeling, it involves tasks such as data visualization, data summary statistics, data cleansing, and data transformation.EDA assists data scientists and analysts in understanding the structure, distribution, and correlations between variables in their data.Python libraries like Pandas for data manipulation, Matplotlib and Seaborn for data visualization, and statistical approaches like mean, median, and standard deviation calculations are common EDA tools.From this process we could show the relation of Attrition to many factors in the dataset and also could show whether there is Attrition or not. Typically, categorical data would be explored in EDA by showing the distribution of categories, computing summary statistics for each category, and investigating correlations between categorical variables and the target variable. We have plotted graphs for various categorical data.

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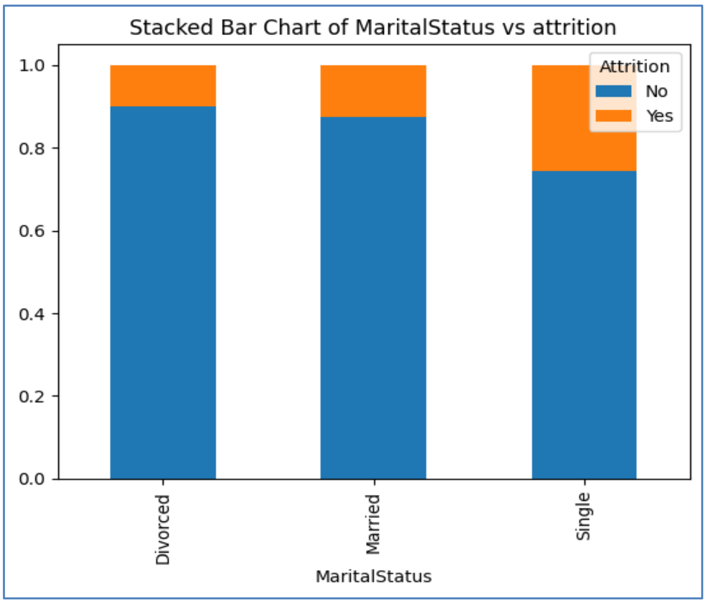
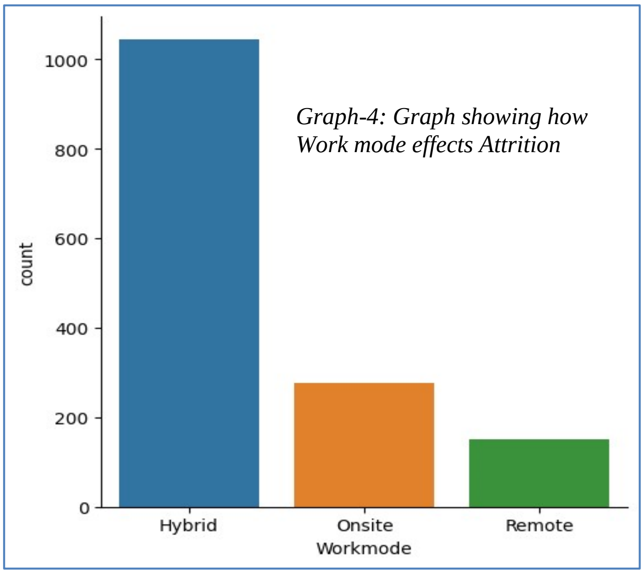
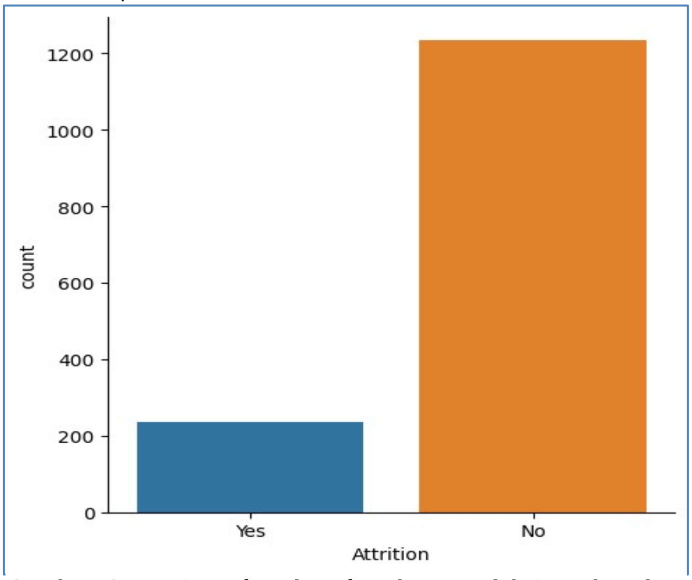


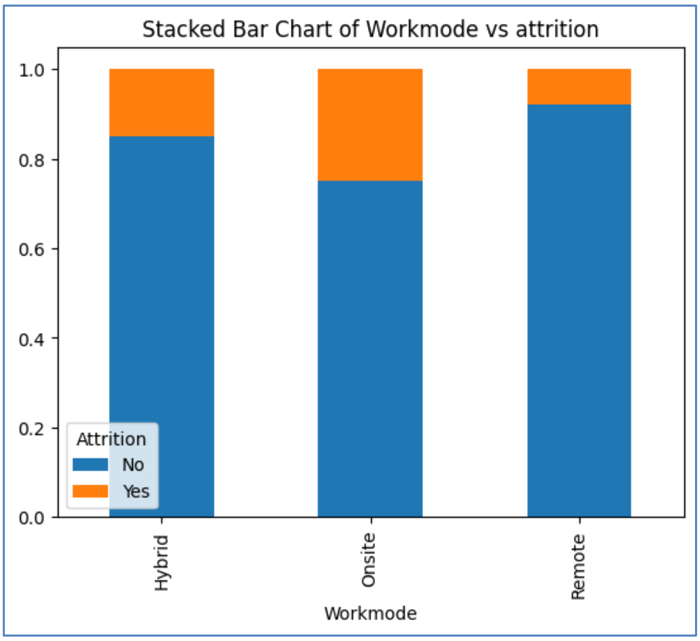
Graph-1: Comparison of Attrition with No Attrition from the dataset



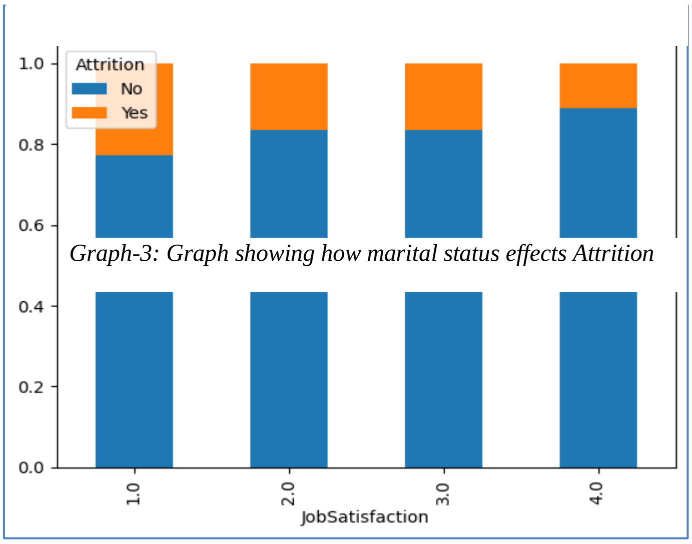
Graph-4: Graph showing how Work mode effects Attrition



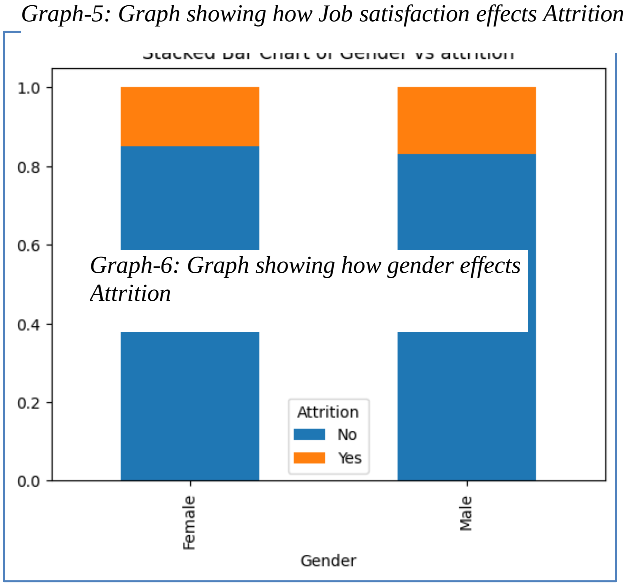
Graph-2: Comparison of number of employees and their work mode



Graph-5: Graph showing how Job satisfaction effects Attrition



Graph-3: Graph showing how marital status effects Attrition



Graph-6: Graph showing how gender effects Attrition

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By further analysis and more visualizations, we could draw the distribution of the features in the dataset, plotted the stacked bar plots to showhow every feature and its distribution has an effect on Attrition. Below are the graphs where, Graph-3 shows the relation of marital status and how its distribution has Attrition difference. We can see that single Employees are more likely to leave the company.Graph-4 shows that employees who are working on-site are more presumed to be resigningSimilarly, Graph-5 captures the relation of Job satisfaction with Attrition and clearly employees with less satisfaction are

Fig-2(a) 16 of the Features contributing to the attrition and the Attrition distribution within every feature.

more interested to find another company and leave the present company.Graph-6 shows that Gender is not a big factor as the results of Attrition vs No attrition are neutral and equal.

The above figure-2(a) shows the Attrition is not more likely on a level of huge excavation or mass resig-nation on few features. The most important features that have more negative effects than others are Over time, Percent salary hike and Years at company.

Figure2(b) The features from this figure are Number of companies worked and Environment Satisfaction

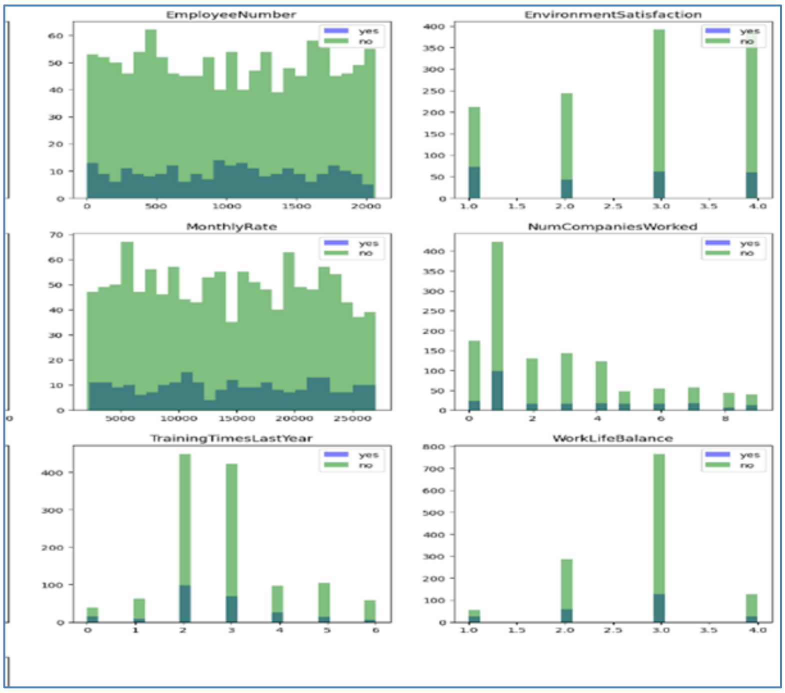


Fig-2(b) 6 more Features contributing to the attrition and the Attrition distribution within every feature.

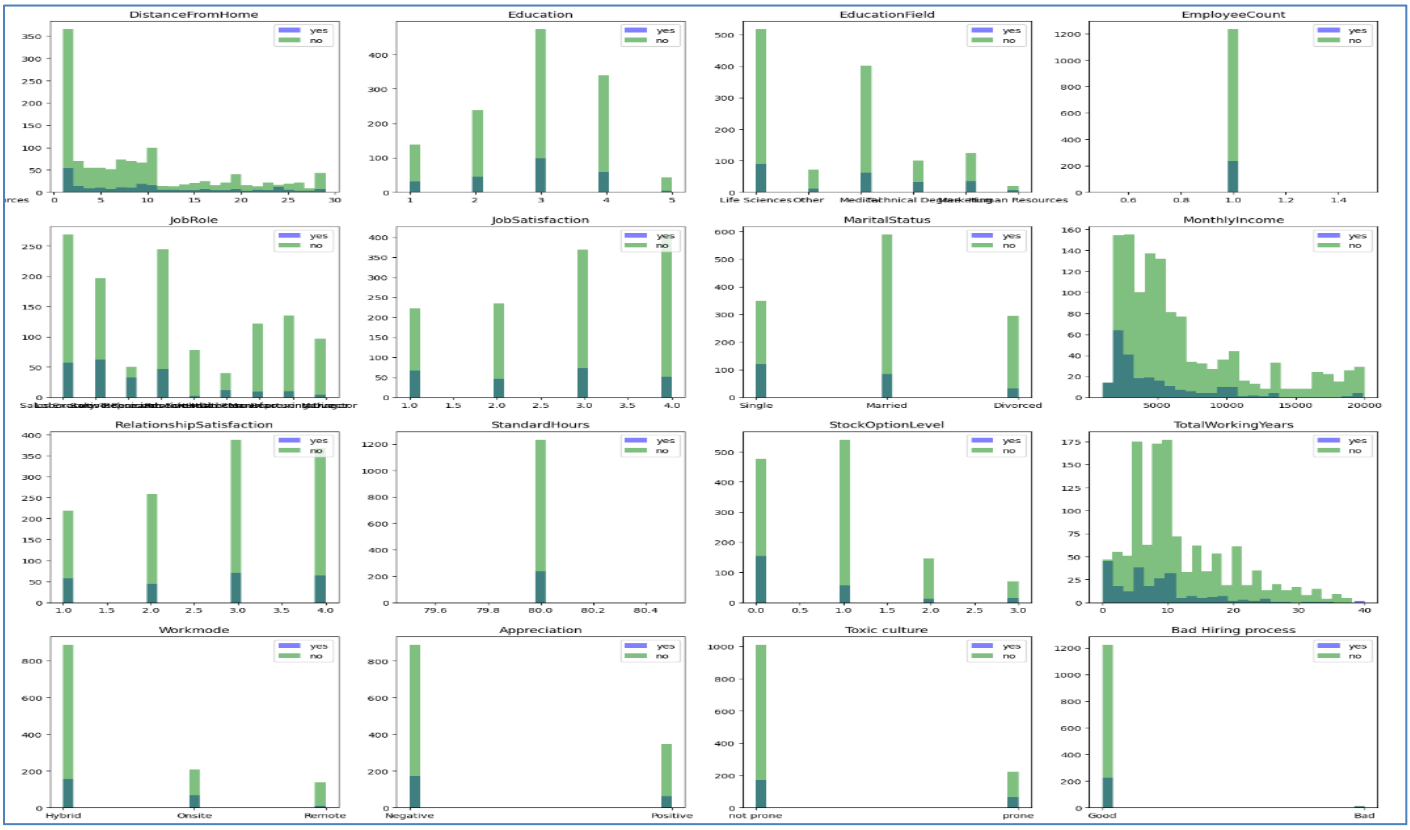


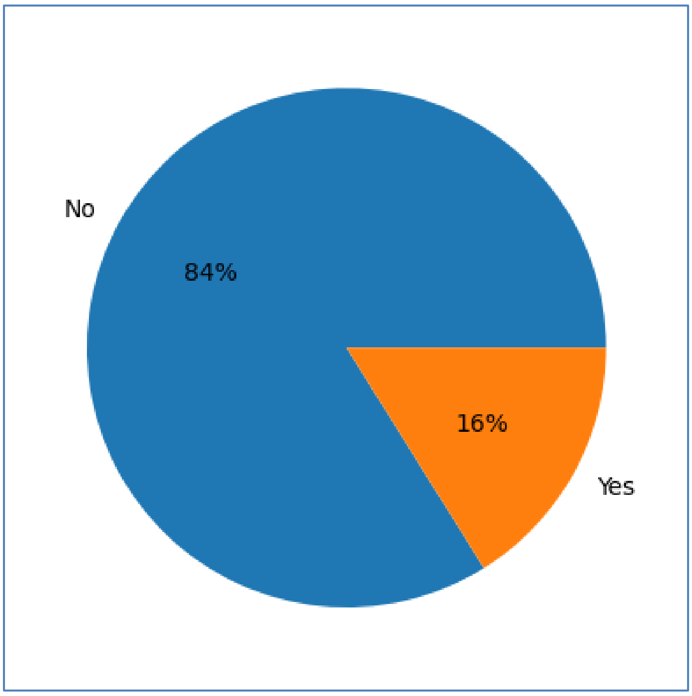
Fig-2(c) 16 of the important Features contributing to the attrition.

Overall, by Analyzing the data and plotting Several graphs, we can conclude that 38 features and their distribution having the negative effect leading to Attrition are less and only few employees are prone to leave the company. We can also observe how employees with less benefits in every factor are more prone to leave the company than the employees with more benefits in the same factors. This analysis definitely helps the HR and management to improve the factors and also to analyze their work force attitude towards the company.

Now after we are done with the EDA process, we develop and explore the deep learning and ensemble models that give the output of Attrition or no Attrition By feature and distribution. We then compare the models and rank the models by how accurately they are detecting the Attrition rate and how much percentage of its detection is accurate of ‘Attrition’ or ‘Not Attrition’.

3.3 Web Interface

To extract valuable information from the pre-processed data, we conducted advanced feature engineering. This step involved creating relevant features and transforming existing ones to enhance the predictive power of our model. Feature engineering allowed us to capture more complex relationships and patterns within the data that might not have been apparent from the raw features.



Graph-7: Pie chart showing the percentage of Attrition that is caused

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4. PROPOSED SYSTEM

The proposed System has three Deep Learning algorithms and three ensemble DL methods. We used Long-Short term Memory algorithm, Sequential feed-forward neural network algorithm and Single Perceptron layer model. The ensemble methods are Bagging, Boosting and Stacking.

To construct the LSTM Model. A Keras sequential model is generated.There are two LSTM layers with 64 units each added. The first LSTM layer produces sequences, whereas the second does not. This is a common arrangement for sequence-to-sequence models.To prevent overfitting, a dropout layer with a dropout rate of 0.2 is introduced. For

binary classification (Attrition prediction), a dense layer with one output unit and a sigmoid activation function is added.The Adam optimizer and binary cross-entropy loss function are used to compile the model. For binary classification problems, binary cross-entropy is often utilized.During training, the accuracy measure is also defined to be monitored.The training and testing data are reshaped to correspond to the LSTM model's expected input shape (3D shape: [samples, time steps, features]).

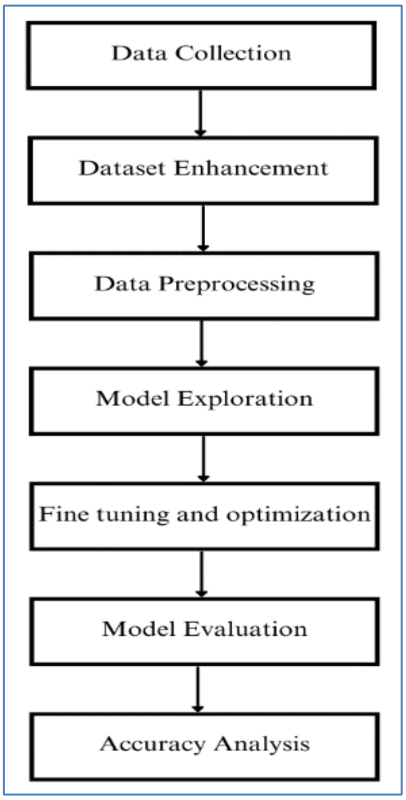

Fig3: Modules in the proposed system

The output informs you about the performance of the LSTM model in terms of its ability to predict employee attrition on the provided test data. The model achieved a test accuracy of approximately 94%, meaning it correctly classified 94% of the instances in the test dataset. For a feedforward neural network with successively stacked layers.The ReLU activation function is used in the input layer, which comprises 69 units (neurons).A hidden layer with 32 units and ReLU activation exists.The output layer contains one unit with a sigmoid activation function, which is appropriate for binary classification.The model is built using the Adam optimizer, a binary cross-entropy loss function (often used for binary classification), and accuracy as a training metric.The model is trained with 75 epochs and a batch size of 65 using the training data. A subset of the training data (30%) is utilized as validation data during training to check the model's performance on data that was not encountered during training.The ReLU (Rectified Linear Unit) activation function is a simple non-linear function commonly used in neural networks. It is defined as:

$$\mathbf{ReLU(x) = max\ (0, x)}$$

Equation 1: ReLU Equation where x is input to the function

The inputs are routed via the ReLU (Rectified Linear Unit) activation function, which is:
output_i = max (0, input i)
where input i represents the weighted sum of the inputs.
The ReLU activation function, like the input layer, is applied to the weighted sum of inputs for each unit in the hidden layer. For a single hidden layer unit:
Input: z = (w1 * output_1) + (w2 * output_2) +... + (w69 * output_69) + b, where w1, w2, ..., w69 are weights, output_1, output_2 ,..., output_69 is input layer outputs, and b is the bias.
The hidden layer's outputs serve as inputs to the output layer.
The sigmoid activation function is used, which compresses the output to the range [0, 1], which can be interpreted as a probability. For the single output layer unit:
Input: z = (w1 * output_hidden_1) + (w2 * output_hidden_2) +... + (w32 * output_hidden_32) + b, where w1, w2,..., w32 are weights, output_hidden_1, output_hidden_2,..., output_hidden_32 are hidden layer outputs, and b is bias.
Output = 1 / (1 + exp(-z)), where exp denotes the exponential function.
The script prints the test loss and test accuracy after training. The accuracy shows how successfully the algorithm can classify employees into either 'Attrition' or 'No Attrition'.The greatest test accuracy is 93%, offering a more interpretable assessment of the model's performance.

The Perceptron class in scikit-learn is used to build a Perceptron model with the following parameters:
max_iter=2000: The maximum number of iterations that the perceptron can perform before converging. This is set at 2000 in order to ensure adequate training.
random_state=42: For reproducibility, a random seed is used.
The fit approach is used to train the Perceptron model using the training data.The trained Perceptron model is used to make predictions on the test data. y_pred holds the projected values.
Using scikit-learn's accuracy_score, the script calculates and prints the accuracy of the Perceptron model on the test data.The output (Y) of a single perceptron in a neural network can be calculated as follows for input features X1, X2,..., Xn, weights W1, W2,..., Wn, and bias (threshold) B:

$$\mathbf{Y = \Sigma\ (Xi * Wi) + B}$$

Equation 2: Single Perceptron layer output equation

Each component of the equation represents the following:

Y: The perceptron's output.
Xi: The value of the input feature for feature i.
Wi denotes the weight associated with the input feature i.
B: A scalar value representing the bias term.

Σ: The summing operator that adds the products of the input characteristics and their weights.

In the case of a single perceptron with input features Age, BusinessTravel, DailyRate,..., Bad Hiring Process, weights w1, w2, w3,..., wN, and bias b can be used to determine the output (Y) as follows:
Y = w1 * Age + w2 * BusinessTravel + w3 * DailyRate +... + wN * Unsatisfactory Hiring Process + b
In this equation, Y represents the perceptron's output, which is the weighted sum of the input features plus the bias.
The dataset's input features include Age, BusinessTravel, DailyRate,..., and Bad Hiring Process.
The weights associated with each input feature are denoted by w1, w2, w3,..., wN.
The bias term, b, is a scalar value.
This weighted total is computed by the perceptron, and the resulting value (Y) is utilized to create a binary classification judgment based on whether Y is positive or negative.
In this code, the best accuracy we could achieve in predicting if employees are going to leave their jobs (attrition) based on the input features is 89%.

A Bagging Classifier is created with the Random Forest classifier as the base estimator and 100 ensemble estimators.
The Bagging Classifier assembles a number of base classifiers, each learned on a different subset of the training data.The Random Forest classifier, which was utilized as the basic classifier, is well-known for its ability to handle complex data and forecast well. The model can prevent overfitting and increase generalization by integrating many Random Forest classifiers in a bagging ensemble.The fit approach is used to train the BaggingClassifier on the training data. This yields a Random Forest classifier ensemble.The trained BaggingClassifier is used to make predictions on the test data.The output of the script is the accuracy of the BaggingClassifier on the test data, which represents the proportion of correctly classified instances in the test dataset. The best accuracy is 88%.

To develop an effective classification Boosting model for forecasting employee attrition, the code makes use of XGBoost, a prominent gradient boosting algorithm. XGBoost is a powerful ensemble learning algorithm that can handle complex data and produce high predicted accuracy.
As the basis learner, an XGBoost classifier is setup with several hyperparameters.The following are important hyperparameters:
booster: Gradient boosting type (in this case, 'gbtree').
max_depth (5): Maximum tree depth.
Learning_rate: The boosting step size shrinking (0.2).
n_estimators: The number of rounds of boosting (100).
subsample: The fraction of samples that were used for fitting (0.8).
colsample_bytree: Feature fraction used for fitting (0.8).
Binary logistic categorization is the goal.
The maximum accuracy that could be achieved through this model is 87%.

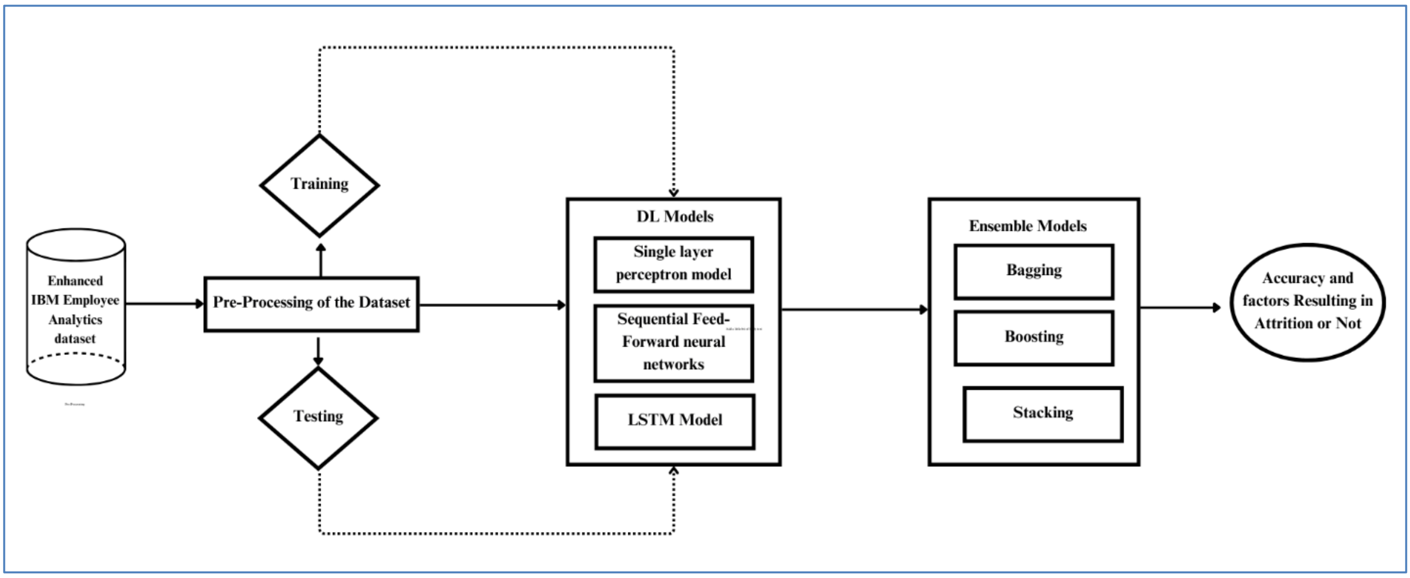

Fig-4: The System Architecture of proposed system

The StackingClassifier from scikit-learn is used to build a stacking model. The basis classifiers and their names are included in the estimator's parameter. The meta-classifier (Logistic Regression) is specified by the final_estimator argument.To boost prediction accuracy, the algorithm implements a stacking ensemble learning technique, which combines various basic classifiers (Random Forest and Gradient Boosting) with a meta-classifier (Logistic Regression). Stacking is a powerful strategy that takes advantage of the benefits of various algorithms.This stacking approach often leads to improved predictive accuracy compared to using individual classifiers. The best accuracy we could achieve here is 87%.

5. Result and Comparison

After optimization, fine-tuning, and multiple iterations, we can finally observe the results provided by the algorithms. The goal is to find a model that can detect whether attrition is present or not, and the result is the percentage by which the proposed models correctly predict the presence of attrition.Here by the EDA methods, we found that the workflow Attrition is present by 16% and No Attrition is present by whopping 84%. The Attrition rates are hence analyzed by the models.

We now see the models and their accuracies of if they can show this accurately:

Table 2: Table showing the comparison multiple models and their accuracies

Deep Learning Model	Best Accuracy
Long-Short Term Memory Algorithm	95%
Sequential Feed-Forward Neural Network	93%
Single-Layer perceptron model	89%
Bagging	88%
Boosting	87%
Stacking	87%

The Single Layer Perceptron model, with an accuracy of 89%, is a simpler model that may be useful for less demanding applications or when computational resources are limited.Both bagging and stacking appear to be equivalent in terms of accuracy, with 88%. Stacking combines the predictions of multiple ensemble methods, whereas bagging is an ensemble technique that improves generality.
dsingle layer perceptron.
The LSTM with the highest accuracy of 95% demonstrates that it is the best at identifying sequential patterns in data. Sequential feed forward works well as well, with a 93% accuracy rate, and is a viable option for activities that do not always require sequential modeling.
The Single Layer Perceptron model, with an accuracy of 89%, is a simpler model that may be useful for less demanding applications or when computational resources are limited.Both bagging and stacking appear to be equivalent in terms of accuracy, with 88%. Stacking combines the predictions of multiple ensemble methods, whereas bagging is an ensemble technique that improves generality.
Boosting, with an accuracy rate of 87%, is slightly less accurate than the other algorithms. More optimization or a more complex ensemble technique would be advantageous.

- Model Selection and Optimization: The choice of ANN and SVM algorithms is guided by their strengths in stroke prediction and classification tasks. Hyperparameter optimization is employed to fine-tune the models and achieve optimal performance.
- Rigorous Testing and Evaluation: Comprehensive testing on a held-out test set ensures that the models' performance is generalizable and reliable. Various metrics, such as accuracy, precision, recall, and F1-score, are used to evaluate the models' effectiveness.
- Ethical Considerations and Data Security: Strict adherence to ethical guidelines and obtaining necessary permissions are paramount. Patient privacy and data security are ensured through robust measures, including de-identification of patient information.

- Clinical Impact and Future Directions: The proposed system empowers healthcare professionals

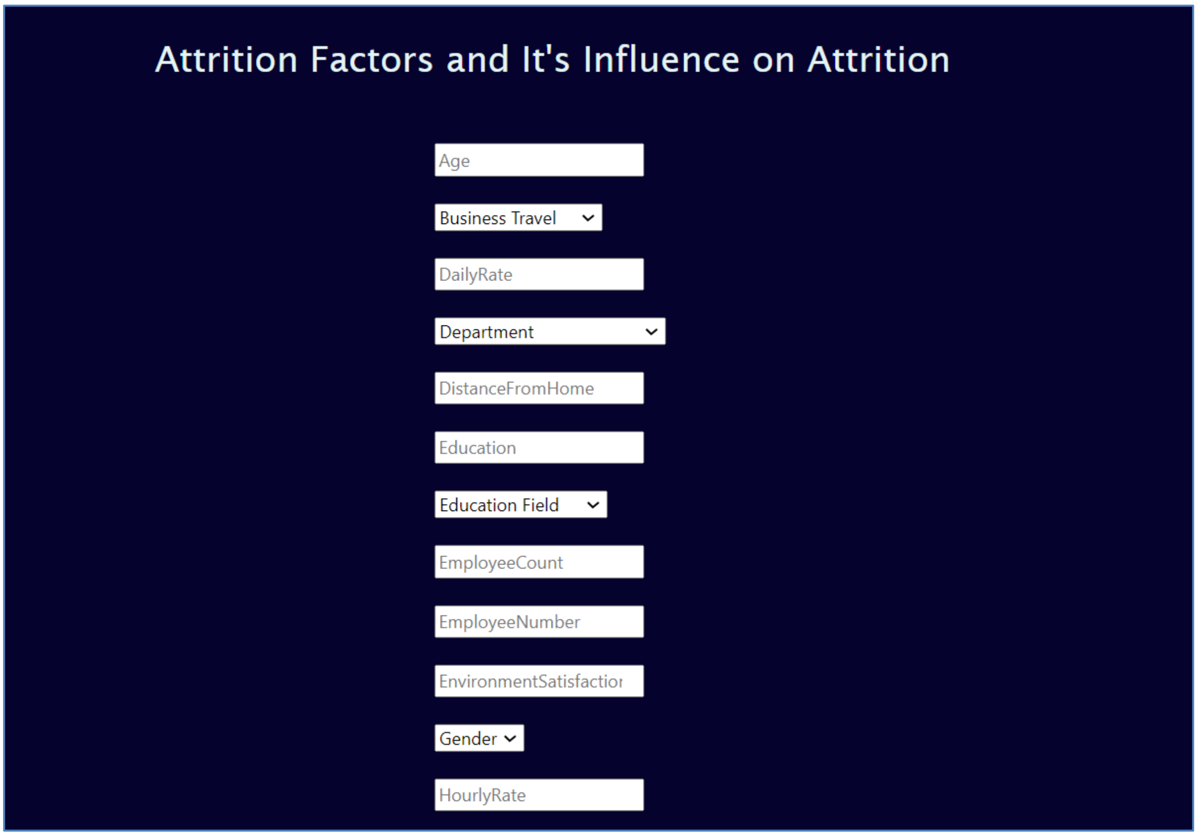

Fig-5: Index page of Web Interface containing Input boxes for giving Factor Values.

with more accurate stroke predictions, potentially leading to improved patient care and treatment outcomes.

Overall, the proposed stroke prediction system represents a significant step forward in addressing the challenge of stroke prediction. The system's superior accuracy, scalability, user-friendly interface, and strong ethical foundation make it a valuable tool for healthcare professionals. The model is trained on a dataset of patient data, including medical records, imaging scans, and clinical features. The model predicts the risk of stroke for each patient, as well as the probability of different stroke types (ischemic stroke, haemorrhagic stroke, and transient ischemic attack).

In the web interface when the inputs are given by the user, then the output is given as Yes or No for Attrition and the percentage of Accuracy with which the result is Correctly detected.The maximum Accuracy by which the Attrition is detected is up to 95%.

6. CONCLUSION

The study aimed to assist the human resources department by providing them with information regarding the likely decision for every employee who would be terminated. The employee is quitting the company. Our proposed model foresees if there is a hidden danger of employee attrition and how well it detects it correctly. The dataset was evaluated to determine the best attributes. that motivate the employee to leave the company. Finally, the optimum model is determined by the job and dataset. LSTM is the strongest performance; however, it may be too difficult for less complex jobs. Single Layer Perceptron models and sequential feed forward models are appropriate alternatives, while ensemble techniques such as stacking, boosting, and bagging can improve resilience and performance even more. This is due to the use of deep learning algorithms, as well as the proper use of pre-processing and selecting the most important features. Stock Option Level, Monthly Income, Job Satisfaction, Job Involvement, and Total Working Years are the greatest top attributes. When a user gives input into the factors, then they could really know the range and how different range of values of the factors are affecting the attrition rate and Our model could detect it properly up to 95%.

The current study was able to answer all of the questions asked regarding the implementation of a model that detects staff attrition with high accuracy. A trade-off between model accuracy and complexity, data qualities, and the issue that's being attempted to solve should all be considered while making this option.

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