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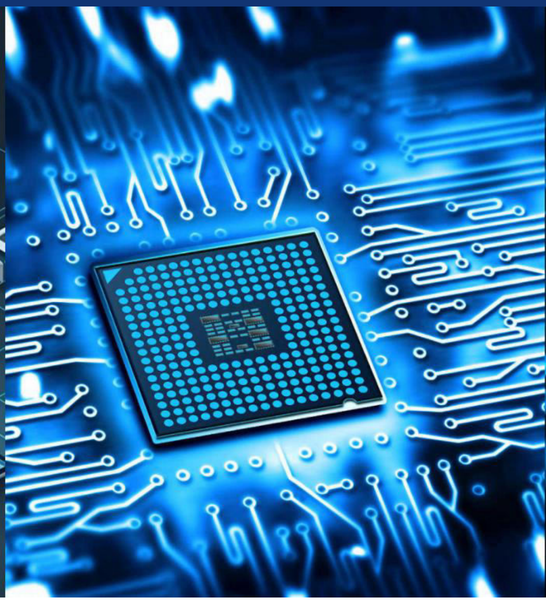


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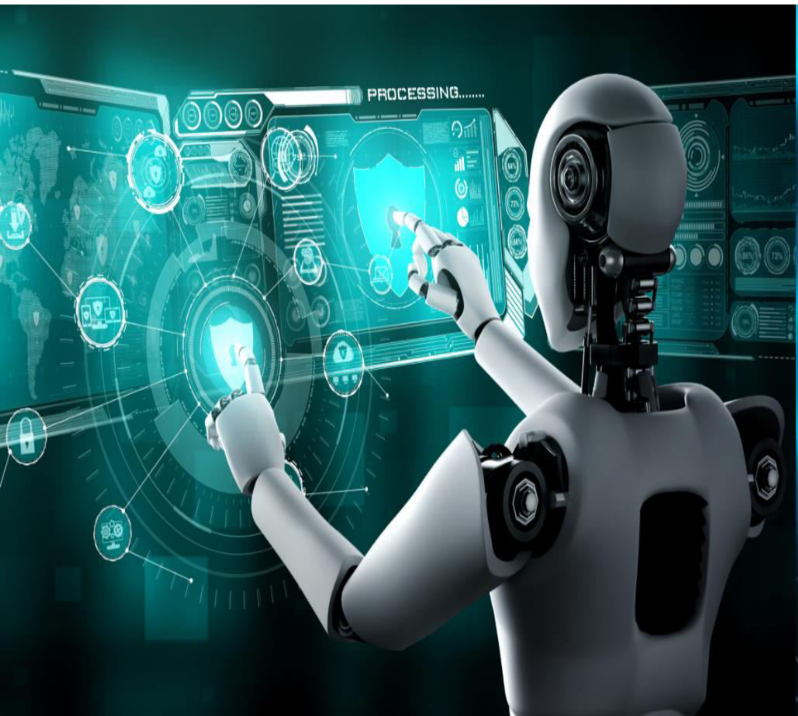

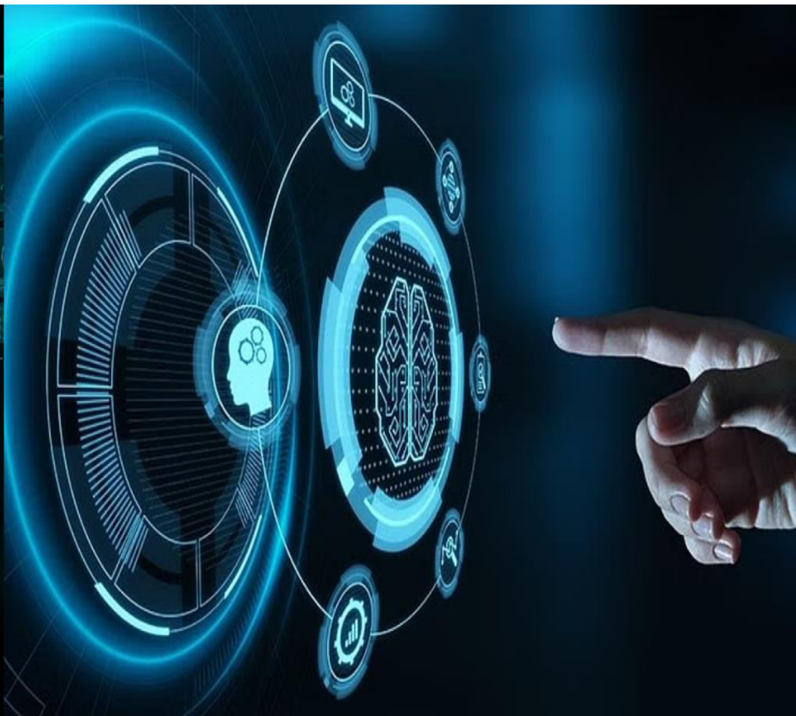

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Financial Risk Assessment using Ensemble Machine Models for Accurate Credit Score

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ABSTRACT: Timely loan repayment along with determining the level of customer reliability is one of the major elements of credit risk assessment. Based on the customer's characteristics credit history analysis and scoring is done. Credit scoring is one of the methods widely used for estimation of the risks associated in granting a loan, or rather the probability of its non-repayment. The combination of increased requirements and the development of advanced new technologies has given rise to a new era: credit scoring using machine learning.

Our FRM_EM credit scoring Model resolves this issue and is more accurate compared to previous designed models as it is ensembled with effective machine learning algorithms like logistic regression, random forest, etc.

KEYWORDS: Financial Risk, Logistic Regression, Decision Tree, Credit Score, Random Forest

I. INTRODUCTION

Financial institutions need to continually weigh the risks of their transactions, and they determine their risk level through credit scoring. Leading up to decades of financial crisis, almost all large banks used credit scoring models based on statistical theories; that crisis, largely brought about by underestimating risk, proved the need for better accuracy in their scoring.

The aim of this project is to develop a robust and accurate financial risk management model by leveraging ensemble learning techniques that combine the predictive power of multiple Machine learning algorithms, including Logistic Regression, K-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes and Random Forests. The model seeks to assess and predict financial risks such as credit default, loan delinquency, and investment instability by analysing historical financial data and identifying high-risk patterns. By integrating ensemble methods, the project aspires to enhance predictive accuracy, reduce model bias and variance, and provide a more reliable decision-support tool for financial institutions and stakeholders.

This paper focusses on Financial risk management, the section II discusses various authors version of their related works, the next section III provides a detailed background on the algorithms used in this project. Section IV introduces the proposed system, detailing the methodology and model architecture. Section V presents comparative results using graphical visualizations, and Section VI concludes the study with insights and future research directions.

II. RELATED WORKS

According to recent studies, ensemble machine learning techniques are increasingly replacing traditional rule-based systems in financial risk assessment. While individual models like Random Forest, K-Nearest Neighbors (KNN), Naive Bayes, and Decision Trees provide varying levels of accuracy in credit scoring, they often face limitations related to overfitting, interpretability, and sensitivity to noisy data. Ensemble methods overcome these challenges by combining multiple models to enhance predictive stability and robustness. To enable accurate and adaptive credit scoring, we have proposed a Risk-Ensemble Framework that integrates Random Forest, KNN, Naive Bayes, and Decision Tree algorithms. This hybrid approach improves the precision of credit evaluations and strengthens financial decision-making.

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Author	Title	Algorithms	Description
Pala et al [1], 2023	Role and Importance of Predictive Analytics in Financial Market Risk Assessment	Predictive models	Future trends and opportunities in the field of predictive analytics for financial market risk assessment, including the integration of artificial intelligence, natural language processing, and blockchain technology are discussed in this study.
Nandipati et al [2], 2024	Credit Card Approval Prediction: A comparative analysis between Logistic Regression, KNN, Decision Trees, Random Forest, XG-Boost	Logistic Regression, K-Nearest Neighbors (KNN), Decision Trees, Random Forests, and XG-Boost	The study utilized a dataset of credit card applications, augmented with Gaussian noise to model real-world uncertainties. Key machine learning models Logistic Regression, K-Nearest Neighbors (KNN), Decision Trees, Random Forest, and XGBoost were evaluated.
Itoo et al [3], 2021	Comparison and analysis of logistic regression, Naïve Bayes and KNN machine learning algorithms for credit card fraud detection	Logistic Regression, Naive Bayes, KNN algorithms	It works effectively only for sampling techniques over the data before developing the prediction model.
Fritz et al [4], 2023	The Role of Machine Learning in Enhancing Risk Management Strategies in Financial Institutions	Modern Portfolio Theory (MPT), Efficient Market Hypothesis (EMH), ML Algorithms	This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection.
Addy et al [5], 2024	Machine learning in financial markets: A critical review of algorithmic trading and risk management	Predictive modelling, Pattern recognition, and Signal generation	The challenges and limitations associated with the adoption of ML in financial markets is addressed. Implemented predictive modelling, pattern recognition, and signal generation for trading purposes using data driven approach
Suneel Sharma et al [6], 2019	Machine learning in banking risk management: A literature review	ML Algorithms, NN Algorithms	The paper seeks to study the extent to which machine learning, which has been highlighted as an emergent business enabler, has been researched in the context of risk management within the banking industry and, subsequently, to identify potential areas for further research.

Table 1 : Literature Review of various ML algorithms pertaining to financial risks.

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III. BACKGROUND

A. Machine Learning Algorithms

Machine learnings models are very effective algorithms. Instead of being programmed with Specific rules, machine learning algorithms are trained on data, allowing them to discover patterns and relationship

1. Logistic Regression

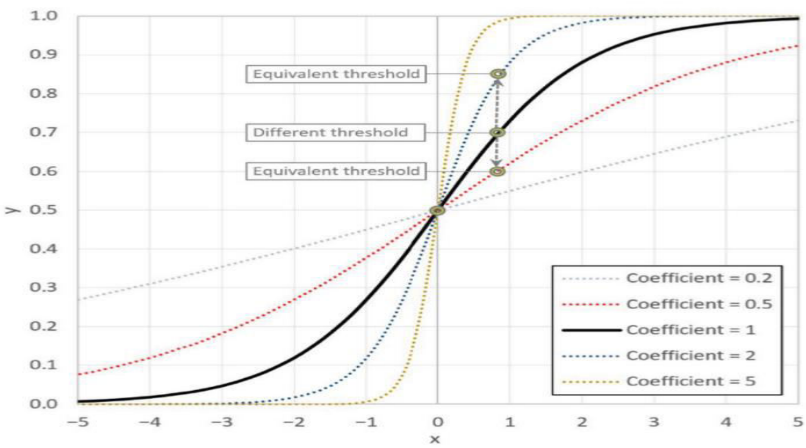

Figure 1 : Logistic Regression

Figure 1 demonstrates the fundamental idea behind the Logistic Regression which is a statistical method used for modelling the relationship between a binary dependent variable (the outcome) and one or more independent variable(s) (predictors). It is used for classification problems where the output is categorical, specifically when the outcome variable has two possible classes (often referred to as 0 or 1, true or false, yes or no). Unlike linear regression, which predicts continuous values, logistic regression predicts the probability of an instance belonging to a particular class. It does this by modelling the log-odds of the probability using a logistic (sigmoid) function, which produces an output between 0 and 1, representing the probability of the instance being in the positive class.

2. Decision Trees

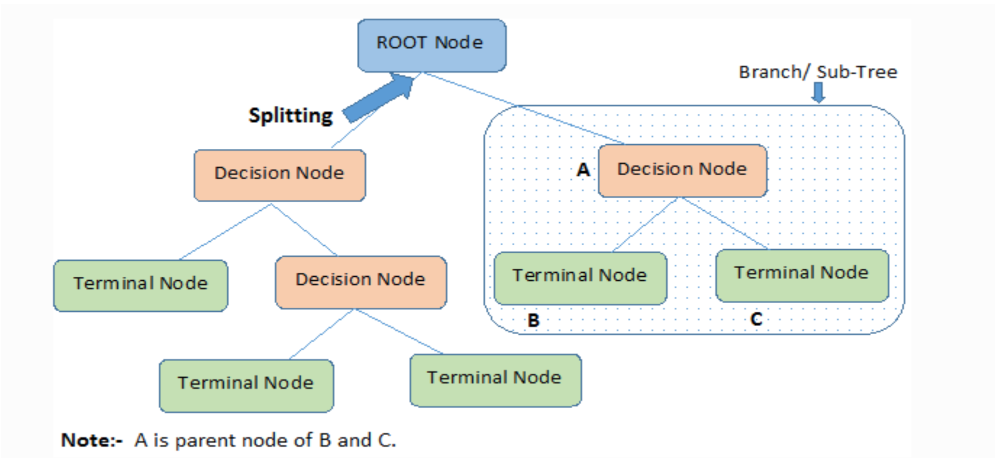

Figure 2 : Decision Tree

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Decision Tree is a supervised machine learning algorithm used for classification and regression tasks. It works by splitting the data into smaller subsets based on different features, making decisions at each node of the tree as shown in *Figure 2*. Each internal node represents a decision rule based on one feature, and each leaf node represents an outcome (a predicted class label or value). The goal is to split the data in such a way that the resulting groups are as pure as possible, meaning that similar data points end up in same group.

3. K-Nearest Neighbors

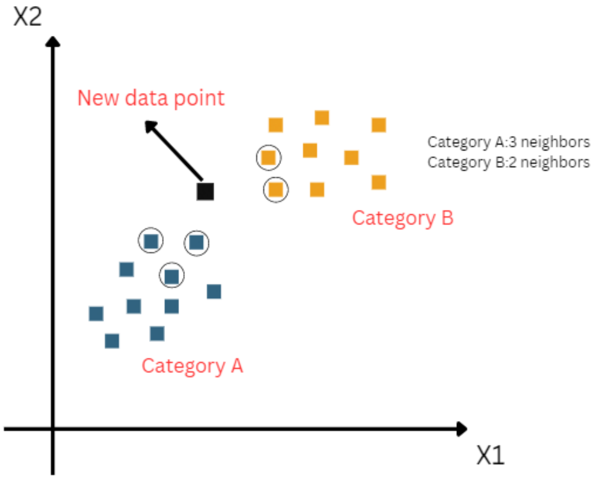

Figure 3 : KNN Algorithm

Figure 3 demonstrates the fundamental idea behind the K-Nearest Neighbors (KNN) algorithm. It is a simple machine learning algorithm used for classification and regression. It works by finding the K closest data points to a given point in the dataset and then making a prediction based on those neighbors. For classification, KNN assigns the most common class among the K Nearest Neighbors. For regression, it takes the average of the K neighbors' values. KNN uses a distance metric, like Euclidean distance, to measure how close the points are to each other. It doesn't require training, as predictions are made directly from the dataset at the time of querying.

4. Naïve Bayes

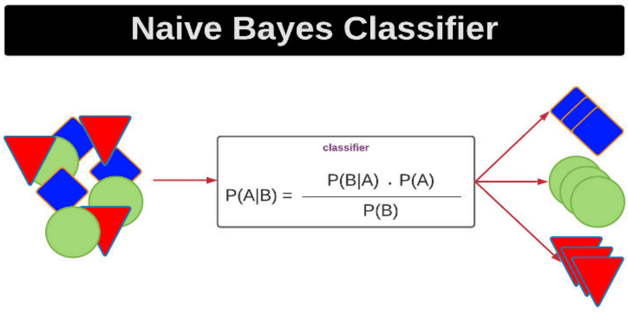

Figure 4 :Naive Bayes Classifier

The Naive Bayes algorithm is a simple, probabilistic classification algorithm based on Bayes' Theorem that makes a strong independence assumption between features. This assumption, while not always true in reality, allows for computationally efficient and surprisingly accurate predictions, particularly in tasks like text classification and spam filtering. As shown in *Figure 4*, the Naïve Bayes classifier' formula is as follows: P(A|B) = P(B|A) * P(A) / P(B)

5. Random Forests

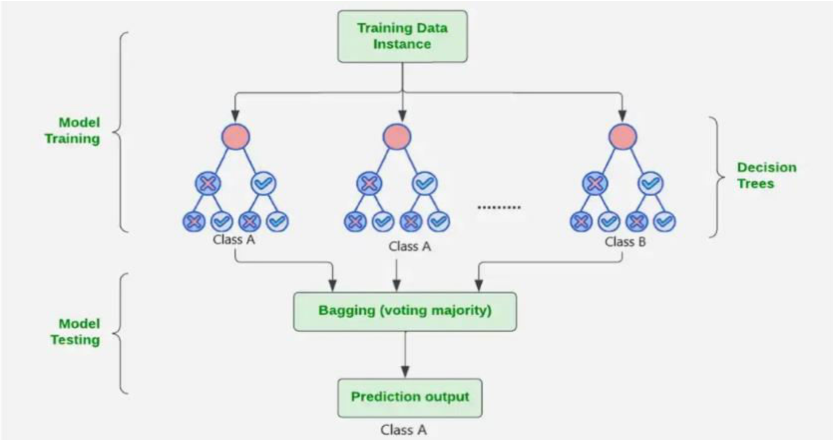

Figure 5 : Random Forests

Figure 4 demonstrates the fundamental idea behind the Random Forest algorithm. It builds an ensemble of decision trees, each trained on a randomly selected subset of the dataset and its features. This randomness results in varied tree structures. Within each tree, the nodes illustrated by branches leading to blue circles indicate decisions based on different feature values. Once all individual trees have made their predictions, the final outcome is determined by combining these results through techniques like majority voting (for classification) or averaging (for regression). This collective decision-making process helps minimize overfitting and boosts the overall accuracy and reliability of the model.

B. Dataset:

In our project we used German-credit score dataset provided by Kaggle for project purpose and it consists of rows: 10,000 attributes 56. The algorithm is efficient enough to handle very large data, but for practical purposes. It is limited to above rows and attributes. In *Table 2*, the attributes are explained in detail.

Column	Type	Description
Age	Numeric	Applicant's age (risk may vary with age-related income stability).
Sex	Categorical	Gender of the applicant. May be used for demographic-based risk patterns (use with fairness in mind).
Job	Categorical (0-3)	Employment type/skill level. Higher skill levels may correlate with more financial security.
Housing	Categorical	Type of housing (own, rent, free) – indicates financial obligation.
Savings Account	Categorical	Saving account status – indicates financial backup.
Checking account	Categorical	Checking account balance – important for current liquidity.

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Credit amount	Numeric	Amount of credit applied for – higher amounts may pose more risk.
Duration	Numeric	Duration of the credit (in months) – longer durations can increase risk.
Purpose	Categorical	Loan purpose (e.g., car, education, radio/TV) – purpose might influence risk patterns.
Risk	Target (Categorical: good, bad)	Label – whether the credit application is a good or bad risk.

Table 2 : german_credit_data dataset

Table 2 presents a dataset financial risk assessment dataset comprising 10,000 records of credit applicants. Each record contains nine input features and one target label. The features include both numerical and categorical variables such as Age, Sex, Job, Housing, Savings account, Checking account, Credit amount, Duration of credit, and Purpose of the loan. The target variable is "Risk," which classifies each applicant as either a "good" or "bad" credit risk. This dataset reflects real-world financial data with missing values in some categorical columns like saving and checking accounts, requiring appropriate preprocessing. The combination of varied feature types makes it ideal for evaluating classification models. Its primary use is to train supervised machine learning algorithms to predict credit risk. Models such as Logistic Regression, K-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes and Random Forests can be effectively applied to this dataset. These models help in identifying patterns and indicators of financial risk. Overall, the dataset is valuable for developing robust ensemble methods in financial risk management. By leveraging ensemble methods, the predictive performance can be enhanced through the combination of multiple algorithms. This ultimately aids financial institutions in making more accurate and data-driven credit decisions.

IV. PROPOSED ALGORITHM

A. *Proposed Architecture:*

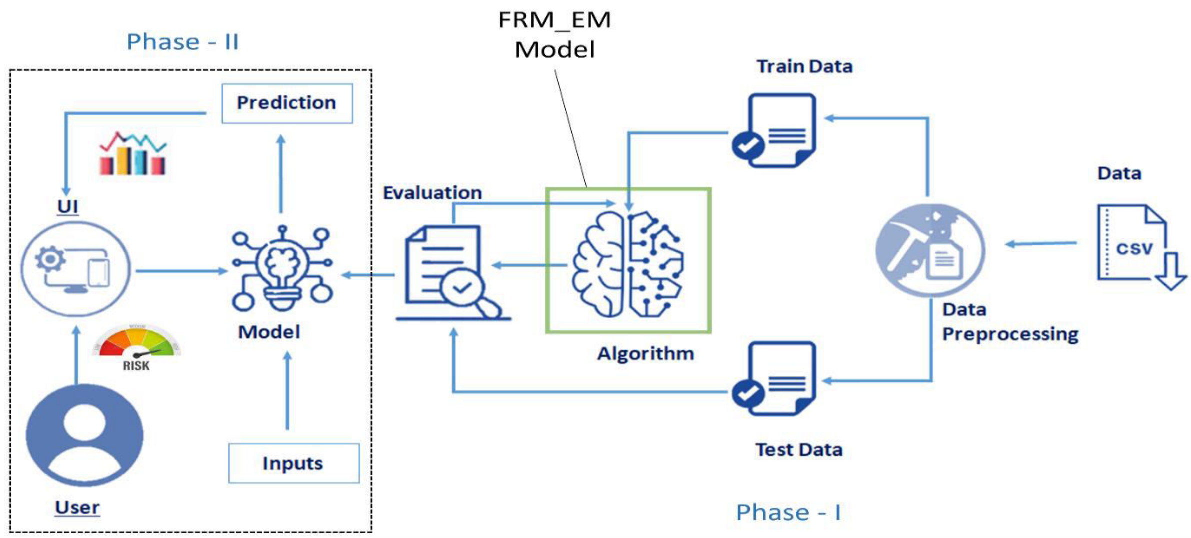

Figure 6 : FRM_EM MODEL ARCHITECTURE

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The working process of the financial risk management system using ensemble methods (FRM_EM model) begins with data collection in CSV format. This raw data undergoes data preprocessing, where missing values are handled, categorical features are encoded, and scaling is applied to prepare the dataset for modeling. The processed data is then split into training and testing datasets. The training data is fed into the FRM_EM model, the accuracy is calculated using Gini index as shown in *eq. (1)*, which consists of an ensemble of algorithms such as Logistic Regression, K-Nearest Neighbors, Decision Trees, Naïve Bayes and Random Forests. These algorithms work together to learn patterns and relationships within the data that are indicative of financial risk. After training, the model is evaluated using the test data to assess its accuracy, precision, recall, and other performance metrics. This evaluation step helps validate the effectiveness of the model before deployment. Once validated, the model is integrated into a user interface (UI). Users can interact with the system by providing relevant input data through the UI. These inputs are processed and passed to the trained model to generate a risk prediction, categorizing applicants as either “good” or “bad” credit risks. The prediction results are displayed back to the user through the UI, supported by visual aids such as charts and risk meters. This interactive loop allows users typically financial analysts or institutions to make informed, data-driven credit decisions. The combination of automation, ensemble intelligence, and a user-friendly interface ensures the system is not only accurate but also accessible and practical for real-world financial risk management.

- **Gini Index Formula:**
  - For a dataset with k classes, the Gini Index is calculated as: Gini = 1 - Σ(pi^2). *eq. (1)*
  - Where:
    - pi is the proportion of class i in the dataset.
    - Σ represents the summation over all classes.

B. *Workflow of the Proposed Algorithm:*

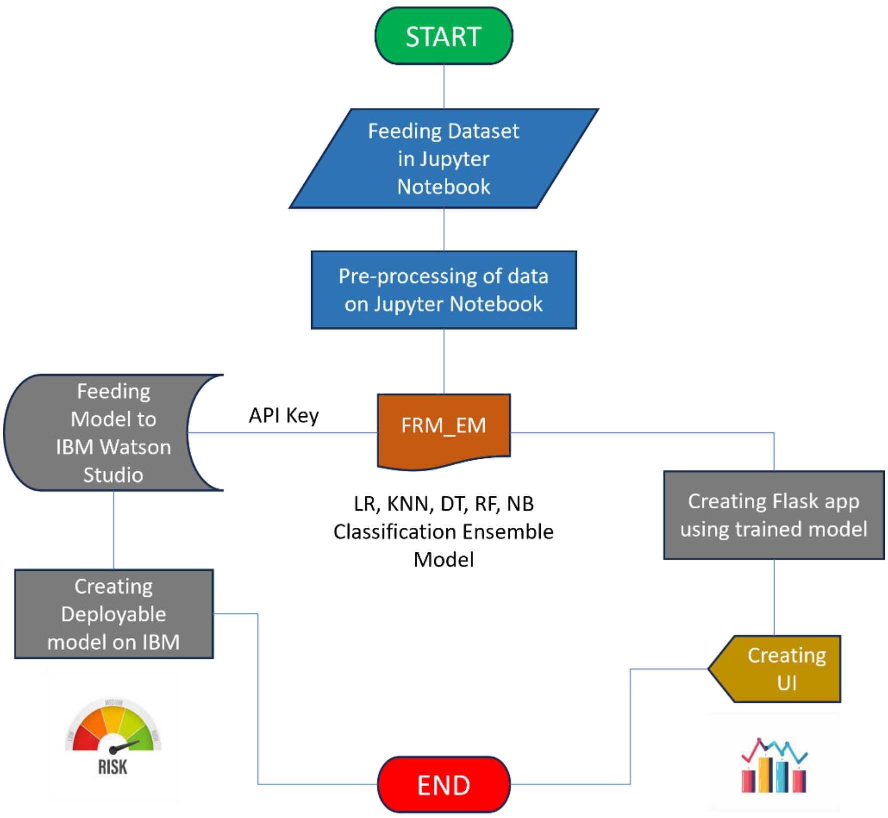

Figure 7 : Workflow of the algorithm

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The process starts by feeding the dataset into a Jupyter Notebook. The data is then preprocessed to handle missing values, encode categories, and scale numerical features. After cleaning, the data is passed to the FRM_EM model, an ensemble classifier using Logistic Regression, KNN, Decision Trees, Naive Bayes and Random Forests. The trained model is then used in two parallel paths. In the first path, it is exported to IBM Watson Studio using an API key to create a deployable risk prediction model. This deployment allows for real-time prediction of financial risk, labeling cases as "good" or "bad". In the second path, the trained model is integrated into a Flask web application. This app is paired with a user interface (UI) that lets users input data and view predictions visually. Both deployment methods aim to make the model accessible and user-friendly. The process ends with the system providing risk predictions that aid decision-making.

V. COMPARISON, RESULTS

The comparison of classification algorithms for financial risk assessment highlights that the ensemble model FRM_EM consistently outperforms others across all metrics. It achieves the highest accuracy (~0.76), followed by Logistic Regression, Random Forest, and Decision Tree, which show similar performance around 0.70. Naive Bayes lags behind with the lowest accuracy (~0.61). In terms of precision, recall, and F1-score, FRM_EM again leads with values above 0.83, reflecting balanced and robust predictions. Random Forest is the next best performer, showing strong scores across the board. KNN, Decision Tree, and Logistic Regression show moderate performance, while KNN records the lowest recall among them. Naive Bayes performs the weakest across all metrics. The results highlight the strength of ensemble methods in capturing complex financial patterns. FRM_EM's high and consistent performance makes it ideal for credit scoring. It offers a more accurate and reliable approach to financial risk assessment than traditional models. Ensemble models leverage the strengths of multiple algorithms to minimize error. This ensures better generalization on unseen data. In high-stakes financial applications, such stability is essential. FRM_EM's performance supports its use in predictive credit scoring systems. It provides a valuable tool for reducing financial risk and improving decision-making.

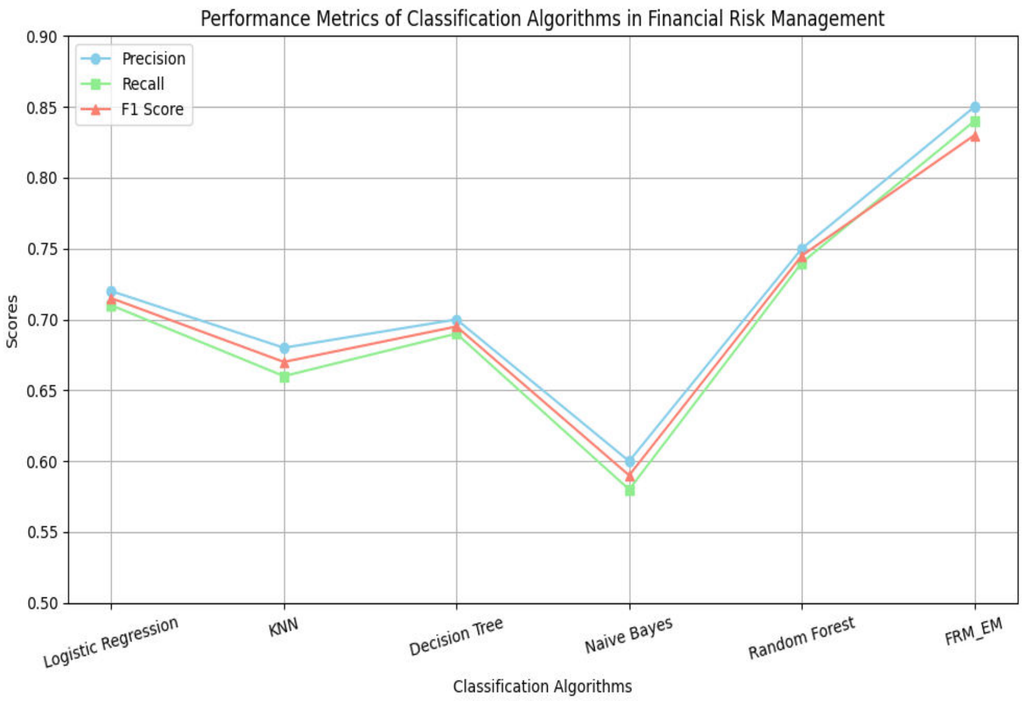

Figure 8 : Performance of each model

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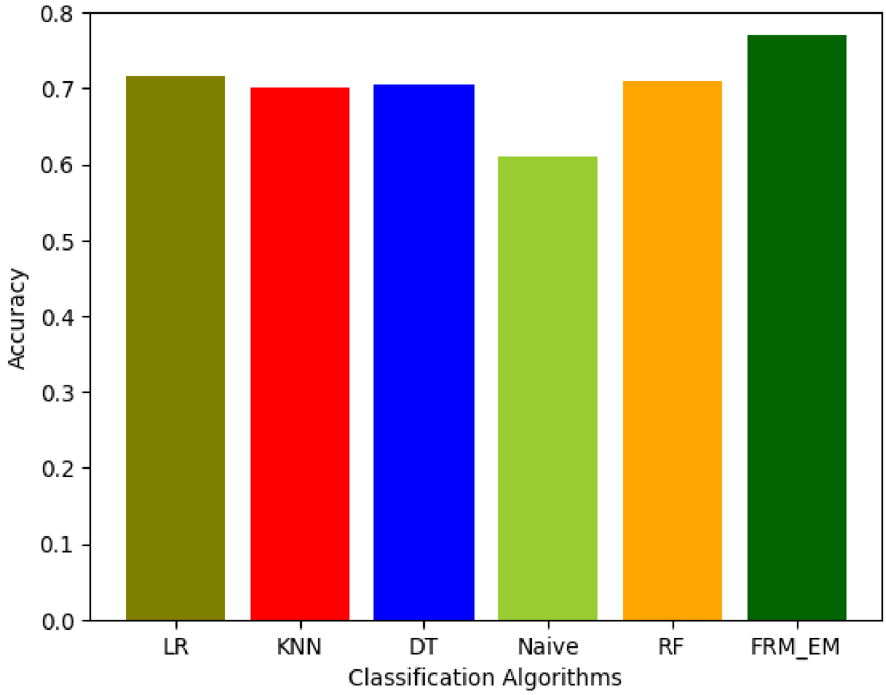

Figure 9 : Accuracy of different classification models

VI. CONCLUSION AND FUTURE WORK

The main objective of this project was to build machine learning algorithms that would be able to identify potential defaulters and therefore reduce company loss. The best model possible would be the one that could minimize false negatives, identifying all defaulters among the client base, while also minimizing false positives, preventing clients to be wrongly classified as defaulters. Meeting these requirements can be quite difficult as there is a tradeoff between precision and recall, meaning that increasing the value of one of these metrics often decreases the value of the other. Considering the importance of minimizing company loss, we decided to give more emphasis on reducing false positives, searching for the best hyperparameters that could increase the recall rate.

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