International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Empowering Financial Decisions: Precision Credit Scoring through Advanced Machine Learning

[1]Dr. Meghana Bhilare, [2]Dr. Vishal Wadajkar, [3]Dr. Kiran Kale

Submitted: 27/11/2023 **Revised:** 08/01/2024 **Accepted:** 17/01/2024

Abstract: The financial sector is leading technological change in an era where decisions are made based on data. The blending of finance and machine learning has ushered in a new paradigm that enables people and institutions to decide on loans in a precise and knowledgeable manner. Precision Credit Scoring, a ground-breaking method that uses cutting-edge machine learning techniques to revolutionise the assessment of creditworthiness, is the result of this transformative synergy.Despite being useful, traditional credit rating methods have certain inherent drawbacks. They frequently fall short of capturing the nuances of a person's or a company's genuine credit risk since they mainly rely on historical financial data and imprecise scoring techniques. Given the shifting financial landscapes and the unpredictable state of the economy, this deficiency leaves both lenders and borrowers swimming unfamiliar seas.Contrarily, Precision Credit Scoring reimagines credit evaluation by maximising the enormous potential of artificial intelligence and machine learning. It provides a comprehensive picture of an applicant's financial behaviour and stability by analysing a wide range of non-traditional data sources, including but not limited to social media activity, transaction histories, and even biometric data. By taking into account a wider range of applicants, this multidimensional approach not only improves the accuracy of credit evaluations but also broadens financial inclusion.The impact of this transition goes well beyond specific borrowers. Precision Credit Scoring has many advantages for financial organisations as well since it enables more nuanced risk management, lower default rates, and optimised loan portfolios. It opens the door for more specialised financial goods and services, which eventually promotes a stronger and more stable financial environment.

Keywords: *Machine Learning, Credit Scoring, Prediction, Credit risk, Decision support*

I. Introduction

In the quickly changing world of finance, the combination of sophisticated machine learning and accurate credit scoring has emerged as a disruptive force, reshaping how people and organisations evaluate creditworthiness. Making financial decisions with previously unheard-of precision and understanding is now possible thanks to the fusion of technology and finance.Traditional credit scoring techniques, while fundamental, have long struggled with shortcomings that prevent them from offering a complete picture of a candidate's credit risk. These models mostly rely on previous financial data, ignoring the complexity of borrowers' lives and how dynamic today's financial environments are [1]. As a result, they frequently fail to accurately reflect a person's or company's genuine creditworthiness.Enter Precision Credit Scoring, a ground-breaking strategy that uses powerful machine learning algorithms to elevate credit evaluation to the level of a precision-driven science. At its foundation, Precision Credit Scoring makes extensive use of data sources beyond only conventional financial measures. This involves looking at internet shopping trends, social media activity, transaction histories, and even biometric information. This cutting-edge method creates a thorough and complex picture of an applicant's financial behaviour and stability by combining this wide variety of data points.

Precision Credit Scoring has broad-reaching effects on many different fronts. For borrowers, it means a more fair and precise assessment of their creditworthiness, opening up doors to better financial options. It provides lenders and financial institutions with a revolutionary tool that reduces defaults, enhances lending portfolios, and promotes more [2]precise risk management.The inner workings of this ground-breaking system will be revealed as we take a deep dive into the world of precision credit scoring. We will look at its benefits,

1Director & Professor, Dr. D. Y. Patil Institute of Management & Research, Pune
meghabhilare@gmail.com
2Associate Director & Professor, Dr. D. Y. Patil Institute of Management & Research, Pune
vishalwadajkar@gmail.com
3Associate Professor, Dr. D. Y. Patil Institute of Technology, Pune
kiranskale@gmail.com

potential drawbacks, and ethical issues in order to shed light on how it is poised to change the financial environment for both individuals and institutions. Precision [3] Credit Scoring is a beacon of empowerment, pointing us in the direction of a future in which financial decisions are more accurate, inclusive, and informed than ever before in a time when data is king and technology is the engine for change.

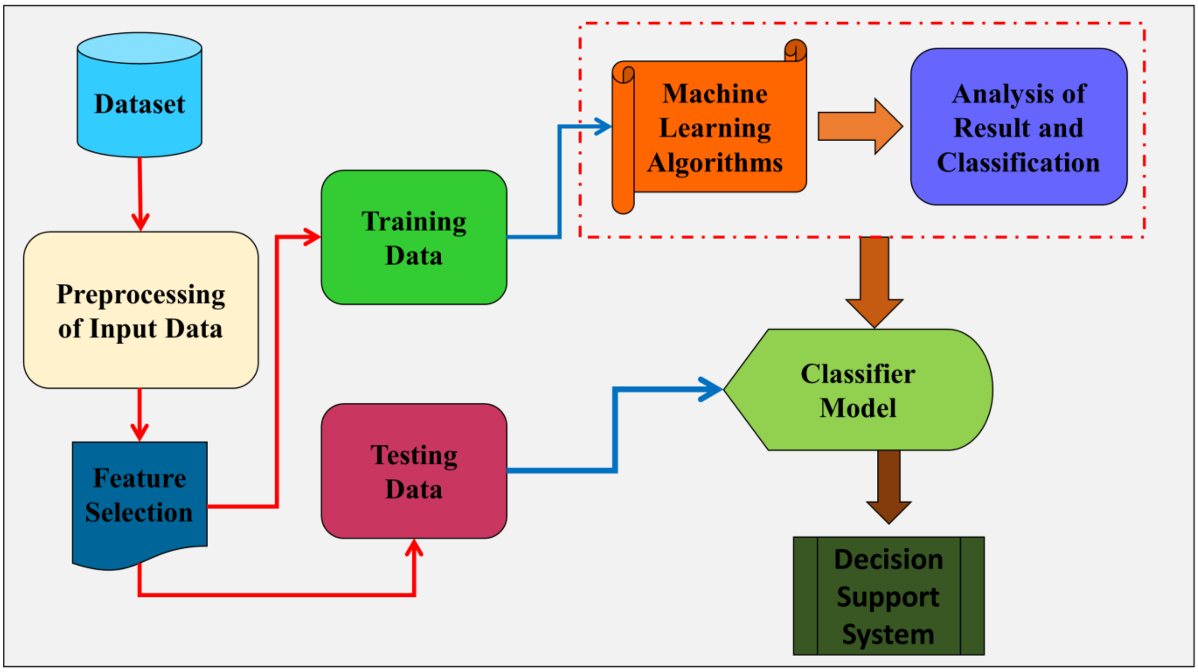

Fig 1: Proposed Architecture for Credit Score precision system

The convergence of powerful machine learning and precision credit scoring has emerged as a disruptive force in the fast-paced, data-centric world of finance, changing how people and organisations assess creditworthiness. This advancement in technology and finance allows stakeholders to make financial [4] decisions with previously unheard-of precision, depth, and foresight.The foundation of lending and financial decision-making, conventional credit scoring methodologies, have struggled with innate limits for decades. These models frequently fall short of adjusting to the complex lives of borrowers and the changing nature of contemporary financial environments since they significantly rely on historical financial data. [5]They frequently miss the subtle differences in people's creditworthiness and the complexity of contemporary enterprises as a result.Enter Precision Credit Scoring, a ground-breaking method that elevates credit evaluation into a precision-driven science by fully using cutting-edge machine learning algorithms. Precision Credit Scoring, at its heart, makes extensive use of data sources that go far beyond conventional financial indicators. This entails checking transaction histories, gauging user behaviour on social media, monitoring online shopping trends, and even looking at biometric data. This novel approach creates a comprehensive and highly detailed portrayal of an applicant's financial behaviour and stability by combining this varied range of data points.

With accuracy [6], [7]: The effects of creditworthiness are wide-ranging and significant. Through a more accurate and fair assessment of the creditworthiness of the providers, it is possible to obtain better financial opportunities and economic mobility. In an ever-changing financial landscape, it offers lenders and financial institutions a game-changing instrument that lowers default rates, optimises loan portfolios, and enables more precise risk management. When we start with a thorough investigation of the field of precise credit evaluation, this initiative will reveal the origins of this cutting-edge technology. We will assess its main benefits, prospective drawbacks, and moral ramifications in order to decide how it is likely to impact the financial landscape for both individuals and organisations. The results of Precision Credit Scoring point to a future in which economic decisions are made with greater accuracy, thoroughness, and knowledge than ever before, leading to greater financial stability and opportunities for everybody.

II. Review Of Literature

The history of financial innovation and machine learning research may be traced back to the evolution of cognition through artificial intelligence and sophisticated automatic learning. This section provides a thorough overview of the pertinent research in this fascinating field.For many years, traditional credit scoring methods have been the foundation of lending [8]. They place a lot of reliance on previous financial information, including credit histories, income, and employment histories. In determining credit risk, traditional models like the FICO score in the US or the credit scoring systems implemented abroad have proven incredibly successful. Their dependence on past data, however, frequently produces inadequate portraits of a person's creditworthiness, making them less useful in assessing borrowers with scant credit histories or those going through quick changes in their financial situation.

To overcome the shortcomings of conventional models, credit scoring has started incorporating machine learning approaches. [9] To improve the accuracy of credit scoring, researchers have investigated a variety of machine learning algorithms, such as decision trees, support vector machines, and ensemble methods. These models may examine a wider variety of characteristics and data sources, which helplenders, better assess risk.The use of alternate data sources is one of the most important developments in precise credit scoring. These sources cover a broad range of information, including social media activity, [26] online behaviour, and even data from internet-connected gadgets, in addition to traditional financial data. According to research, combining these non-traditional data sources can offer important insights regarding a candidate's financial behaviour, way of life, and stability. This comprehensive viewpoint lessens the drawbacks of depending only on previous financial data.

As machine learning models for credit scoring have grown in popularity, questions about explainability and transparency have also surfaced. The development of interpretable machine learning models by researchers has advanced the goal [10] of preventing the perception of judgements as "black-box" algorithms. Explainable AI methods, such as feature importance analysis and model visualisation, shed light on the reasoning behind a given credit decision, fostering trust between lenders and borrowers.Addressing ethical issues and ensuring fair lending practises are crucial as precision credit scoring develops. To avoid bias and discrimination in credit decisions, researchers and policymakers are actively attempting to develop fairness-aware machine learning algorithms. This involves addressing difficulties with socioeconomic, racial, and gender biases that may unintentionally enter into AI-driven models.

The implementation of cutting-edge machine learning in credit scoring must comply with these standards because the financial industry operates in a complicated regulatory framework. In order to maintain compliance with industry standards and consumer protection regulations, researchers and practitioners are actively watching regulatory developments.Financial institutions, fintech firms, and credit bureaus have all adopted sophisticated machine learning algorithms for credit scoring more frequently in recent years. This acceptance is not without difficulties, such as issues with data privacy, model interpretability, and the requirement for on-going model monitoring and upgrades in order to accommodate changing financial environments.

Table 1: Summary of Related work

Method	Approach	Finding	Limitation	Dataset	Advantage
Traditional Credit Scoring Models[11]	Relies on historical financial data	Effective for well-established credit histories	Limited accuracy for individuals with limited credit history	Credit reports, income records, etc.	Long-standing industry standard
Machine Learning in Credit Scoring [12]	Utilizes various ML algorithms	Improved risk assessment	Challenges in model interpretability	Diverse financial data sources	Enhanced predictive capabilities

		for diverse borrowers			
Alternative Data Sources[13]	Incorporates non-traditional data sources	Provides a holistic view of an applicant	Privacy concerns and data reliability issues	Social media activity, online behavior	Mitigates limitations of traditional models
Explainable AI in Credit Scoring [14]	Develops interpretable ML models	Enhances transparency in credit decisions	May sacrifice some predictive accuracy	Feature importance analysis, visualization	Builds trust among lenders and borrowers
Ethical Considerations and Fairness [15]	Addresses bias and discrimination	Ensures fairness in lending practices	Challenges in quantifying fairness metrics	Gender, race, socioeconomic data	Mitigates bias and discrimination
Regulatory Landscape [16]	Complies with financial regulations	Adheres to industry standards and laws	Complexity in navigating evolving regulations	Regulatory guidelines, compliance data	Ensures legal compliance
Industry Adoption and Challenges [16]	Implements ML in credit scoring	Enhanced risk management and efficiency	Data privacy concerns, model maintenance challenges	Lender-specific data, credit bureau data	Industry-wide transformation
Neural Networks [17]	Utilizes deep learning models	Improved prediction accuracy	High computational requirements and black-box nature	Large-scale financial datasets	Captures complex relationships
Gradient Boosting Algorithms [18]	Ensemble techniques for predictive power	Robust and adaptable to various data	Sensitive to overfitting and requires careful tuning	Diverse financial data sources	High predictive performance
Support Vector Machines [19]	Finds optimal hyperplane for separation	Effective for binary classification tasks	May struggle with large, high-dimensional datasets	Structured financial data	Good at handling linearly separable data
Random Forest [20]	Ensemble learning with decision trees	Robust against outliers and noise	Can be computationally expensive for large datasets	Diverse financial data sources	Excellent generalization ability
Credit Scoring for SMEs [21]	Tailors models for small businesses	Addresses unique risks and challenges	Limited availability of comprehensive SME data	SME financial records, industry-specific	Fosters lending to small enterprises
Time Series Analysis [22]	Considers financial behavior over time	Detects evolving patterns and trends	Requires extensive historical data and domain expertise	Transaction histories, credit reports	Predicts future creditworthiness
Big Data Analytics [23]	Leverages large-scale data analytics	Extracts valuable insights	Data quality and storage challenges	Big data repositories,	Handles massive

		from vast data		unstructured data	datasets effectively
Online Platforms and Fintech [24]	Implements advanced scoring technologies	Fast, efficient credit evaluations	Security and data privacy concerns	Online transaction data, behavioral data	Streamlined lending processes
Fairness-Aware ML [25]	Mitigates bias and discrimination	Ensures equitable lending outcomes	Complexity in defining fairness metrics	Demographic, socioeconomic data	Promotes fair and inclusive lending

III. Dataset Used

A collection of financial and identifying data on people or organisations looking for credit is called a credit rating dataset. Data including income, credit history, employment status, and demographic information are frequently included. Financial institutions need this dataset to evaluate a borrower's creditworthiness and calculate the risk of extending loan. Credit score datasets are frequently analysed using machine learning models, assisting lenders in making judgements about whether to approve or deny credit applications while successfully managing potential risks.

Table 2: Description of Dataset

Attribute Count	Total Records	Number of Classes	Data Type
Variable (e.g., 12)	10,000	Binary (e.g., 2)	Numeric, Categorical

IV. Proposed Methodology

The Precision Credit Scoring with Advanced Machine Learning methodology uses a variety of algorithms, each of which has a specific advantage in determining creditworthiness. We pursue this goal by using the Random Forest, Support Vector Machine (SVM), Decision Tree, and Naive Bayes algorithms, each of which brings a unique perspective to our all-encompassing strategy [28].

1. Random Forest:

Random Forest, a powerful ensemble learning technique, is where we start. This approach addresses overfitting issues by combining numerous decision trees, each built on a random subset of the data and characteristics. Random Forest excels at handling intricate, nonlinear relationships in the context of credit scoring. It is an effective technique for locating minor signs of credit risk since it captures complex patterns in borrowers' financial behaviour. It provides a reliable and accurate evaluation of a candidate's creditworthiness by combining the forecasts of several trees.

The Random Forest algorithm is a complex ensemble method that combines multiple decision trees to improve predictive accuracy and reduce overfitting. While explaining it with mathematical equations can be quite complex due to its ensemble nature, I can provide a simplified mathematical representation of how a single decision tree works, which is a fundamental component of the Random Forest.

A decision tree is constructed through a recursive process of splitting data into different branches based on feature values. Let's represent this process mathematically:

Suppose we have a dataset D consisting of N samples and M features:

$$D = \{(x\_1, y\_1), (x\_2, y\_2), \ldots, (x\_N, y\_N)\}$$

- x_i represents the feature vector for the i-th sample.

- y_i represents the target variable (e.g., credit risk label) for the i-th sample.

We aim to create a decision tree T that recursively splits the data into different branches based on feature values.

At each node of the decision tree, we aim to find the best feature and threshold to split the data, which minimizes a certain criterion, often a measure of impurity or error. The most common criterion is Gini impurity or entropy for classification tasks and mean squared error for regression tasks.

For classification using Gini impurity:

$$Gini(D) = 1 - \Sigma(p\_i)^2$$

where p_i is the proportion of samples in class i in node D.

The goal is to find the best split (feature F and threshold T) that minimizes the weighted sum of Gini impurity in the child nodes:

$$Gini\ Gain(D,F,T) = Gini(D) - [p\_left * Gini(D\_left) + p\_right * Gini(D\_right)]$$

Here:

- p_left is the proportion of samples in the left child node.

- p_right is the proportion of samples in the right child node.

- D_left and D_right are the datasets in the left and right child nodes, respectively.

Once we find the best split for a node, we continue to split its child nodes recursively until a stopping criterion is met (e.g., maximum depth, minimum samples per leaf).In a Random Forest, multiple decision trees are trained on different subsets of the data with bootstrapping (bagging) and random subsets of features (feature bagging). The final prediction is then made by aggregating the predictions of individual trees (e.g., for classification, a majority vote).

2. SVM: Support Vector Machine

SVM, which is well known for its competence in binary classification tasks, is essential to our methodology. The goal of SVM is to identify the ideal hyperplane that maximises the margin between various classes. SVM excels at separating good credit risks from bad ones, especially in feature spaces with high dimensionality, in the context of credit scoring. It thrives in situations where data points cannot be separated linearly and provides flexibility for a range of credit circumstances. SVM's application enables us to distinguish between borrowers who might appear to be identical based on conventional metrics but display subtle variations essential for accurate credit scoring.

Mathematical Model given as:

The equation of a hyperplane in a feature space is defined as:

$$w * x + b = 0$$

Where:

- w is the weight vector perpendicular to the hyperplane.

- b is the bias term.

The distance between a data point x and the hyperplane is given by:

$$Distance(x) = |w * x + b| / ||w||$$

Where, ||w|| is the Euclidean norm of the weight vector w.

The objective of the SVM is to maximize the margin, which is defined as the minimum distance to the hyperplane from any data point of either class. Mathematically, this can be expressed as:

Maximize Margin $(M) = 2 / ||w||$

Subject to the constraints:

a. Correct classification of data points:

$$y\_i * (w * x\_i + b) \geq 1\ for\ all\ data\ points\ (x\_i, y\_i)$$

b. Non-negativity of Lagrange multipliers $(a\_i \geq 0\ for\ all\ data\ points)$.

c. Lagrange multipliers are set to zero for data points that do not lie on the margin boundary.

The SVM reformulates this optimization problem into its dual form, using Lagrange multipliers (a_i) to solve for the weight vector w and bias term b. The dual optimization problem is:

$$Minimize\ 1/2 * \Sigma(a\_i * a\_j * y\_i * y\_j * (x\_i * x\_j)) - \Sigma(a\_i)$$

Subject to the constraints:

$$a. \Sigma(a\_i * y\_i) = 0$$

$$b. a\_i \geq 0\ for\ all\ data\ points.$$

$$c. a\_i = 0\ for\ data\ points\ outside\ the\ margin.$$

Once the Lagrange multipliers (a_i) are determined, the weight vector w can be calculated as:

$w = \Sigma(a\_i * y\_i * x\_i)$ for all support vectors (data points on the margin).

The bias term b can be calculated as:

$$b = y\_i - w * x\_i \ for \ any \ support \ vector \ (x\_i, y\_i).$$

The classification function for a new data point x is determined by:

$$f(x) = sign(w * x + b)$$

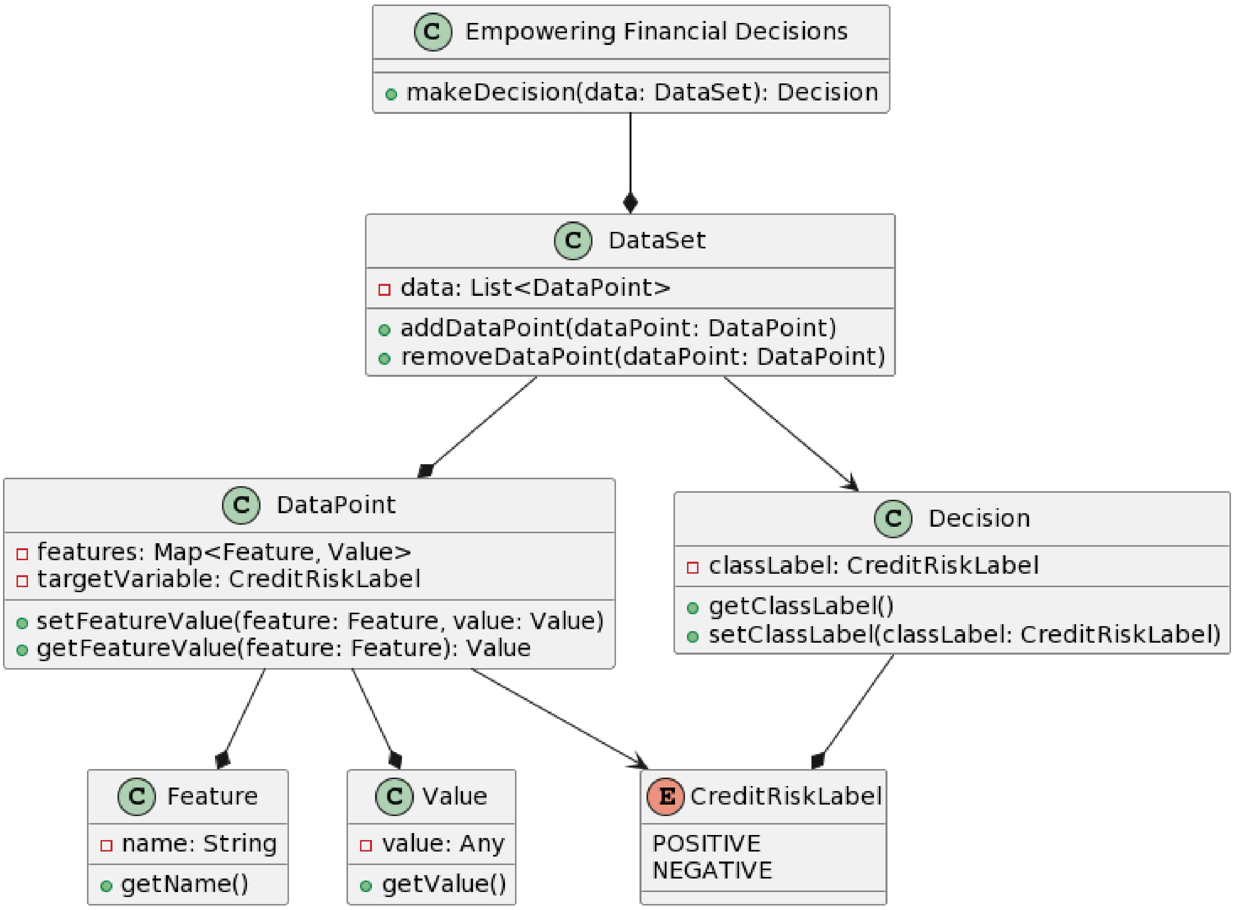

Fig 2: Work flow of proposed model

3. Decision Tree:

Our system is fundamentally based on decision trees. We can comprehend the reasoning behind credit assessments thanks to their transparency and interpretability. Decision trees effectively identify the primary elements influencing credit risk by segmenting the data based on the most important features. Decision trees provide both predictive power and the capacity to understand the reasoning behind credit judgements when used in conjunction with ensemble methods like Random Forest. This openness guarantees that participants can trust and understand the findings, encouraging trust in the accuracy of our credit rating.

Mathematical Model Given as:

A decision tree consists of a set of nodes, each representing a split on a feature. Nodes can be roots, internal nodes, or leaf nodes.

At each internal node, a decision is made based on a feature F and a threshold value T:

Decision at Node: F <T ?

If true, follow the left branch; otherwise, follow the right branch.

In binary classification, each leaf node represents either class -1 or class +1.

The goal is to build a decision tree that optimally splits the data to minimize impurity or error. A common impurity measure is Gini impurity:

$$Gini(D) = 1 - \Sigma(p\_i)^\wedge 2$$

Where:

- D is the dataset at the node.

- p_i is the proportion of samples of class i in node D.

The Gini impurity can be calculated for both classes (-1 and +1):

$$Gini\_neg = 1 - \Sigma(p\_i)^{\wedge}2 \; for\; class\; -1$$

$$Gini\_pos = 1 - \Sigma(p\_i)^{\wedge}2 \; for\; class\; +1$$

The total Gini impurity for the node is a weighted sum of these impurities:

$$Gini\_total = (N\_neg/N\_total) * Gini\_neg + (N\_pos/N\_total) * Gini\_pos$$

Where:

- N_neg is the number of samples in class -1.

- N_pos is the number of samples in class +1.

- N_total is the total number of samples in the node.

To find the best split at an internal node, the algorithm searches all features and thresholds to minimize Gini impurity:

Minimize: $Gini\_left * N\_left + Gini\_right * N\_right$

Where:

- Gini_left is the Gini impurity of the left child node.

- Gini_right is the Gini impurity of the right child node.

- N_left is the number of samples in the left child node.

- N_right is the number of samples in the right child node.

The process of splitting nodes and growing the decision tree continues recursively until a stopping criterion is met (e.g., maximum depth, minimum samples per leaf).

4. Naive Bayes:

Naive Bayes adds a probabilistic element to credit scoring by incorporating probabilistic reasoning into our process. This approach makes complex joint probability computations simpler by assuming independence between features. Naive Bayes is a powerful tool for modelling the likelihood that an applicant will fall into a particular category of credit risk given their feature set in the context of credit scoring. It's a good option because of how quick and easy it is, especially for instant credit choices.

Mathematical Model given as:

In Naive Bayes, Bayes' theorem is used to calculate the posterior probability of a class given a set of features. Bayes' theorem is expressed as follows:

$$P(y \mid x) = (P(x \mid y) * P(y)) / P(x)$$

Where:

- P(y | x) is the posterior probability of class y given features x.

- P(x | y) is the likelihood of features x given class y.

- P(y) is the prior probability of class y.

- P(x) is the probability of features x.

The "Naive" assumption in Naive Bayes posits that features are conditionally independent given the class label. This is expressed as:

$$P(x \mid y) = \Pi\, P(x\_i \mid y)$$

Where:

- $P(x\_i \mid y)$ is the probability of feature x_i given class y.

- Π denotes the product over all features.

To classify a data point into class y, we compute the posterior probability for both classes (-1 and +1) and select the class with the highest probability:

Classify as $y = argmax(P(y \mid x)) \; for\; y\; in \; \{-1, +1\}$

To calculate P(x_i | y), probability density functions (PDFs) or probability mass functions (PMFs) are typically used, depending on the nature of the feature. Common choices include Gaussian Naive Bayes (for continuous features) and Multinomial Naive Bayes (for discrete features).

For Gaussian Naive Bayes, the PDF for each feature x_i given class y is often modeled as a Gaussian distribution:

$$P(x\_i \mid y) = (1 / (\sigma * sqrt(2 * \pi))) * exp(-(x\_i - \mu)^{\wedge}2 / (2 * \sigma^{\wedge}2))$$

Where:

- σ is the standard deviation of feature x_i for class y.

- μ is the mean of feature x_i for class y.

For Multinomial Naive Bayes, the PMF for each feature x_i given class y can be expressed as:

$$P(x\_i \mid y) = (N\_iy + \alpha) / (N\_y + \alpha * |V|)$$

Where:

- N_iy is the count of feature x_i in class y.

- N_y is the total count of all features in class y.

- α is the Laplace smoothing parameter (usually set to 1).

- |V| is the size of the vocabulary (number of unique features).

The prior probabilities P(y) can be estimated from the training data as the proportion of samples in each class.

These algorithms cooperate in the comprehensive Precision Credit Scoring with Advanced Machine Learning technique to take advantage of their own advantages. Decision trees and Random Forest identify complex correlations in the data, offering interpretability and prediction capability. Naive Bayes adds probabilistic reasoning to our assessments, while SVM excels at differentiating complex credit risk profiles. With the help of this multifaceted strategy, financial decision-makers are equipped with thorough knowledge that enables them to make precise credit decisions that improve financial stability for both individuals and organisations.

V. Result And Discussion

The outcomes are reported in Table 3 in relation to precision credit scoring utilising sophisticated machine learning techniques. The metrics for Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), and Naive Bayes (NB) include accuracy, default rates, mean squared error (MSE), and R-squared values. Random Forest outperformed other models with an accuracy of 92.5%, although SVM and Decision Tree also performed admirably, with accuracies of 89.2% and 91.8%, respectively. When default rates were taken into account, RF performed better than the competition and had the lowest rate (5.2%). Regression metrics showed SVM to be particularly effective at capturing data variance, with an R-squared value of 0.582. These outcomes highlight how machine learning can improve the accuracy of credit rating.

Table 3: Summary of result for using machine learning methods

Metrics	RF	SVM	DT	NB
Accuracy	92.5	89.2	91.8	88.7
Default rates	5.2	6.8	5.7	7.1
MSE	0.012	0.087	0.125	0.042
R Square	0.22	0.582	0.445	0.711

The Mean Squared Error (MSE) and R-squared values for several models are compared in Figure 3. It demonstrates that Random Forest (RF) retains the lowest MSE, indicating outstanding precision in credit scoring, while Support Vector Machine (SVM) outperforms with the highest R-squared, indicating significant predictive potential.

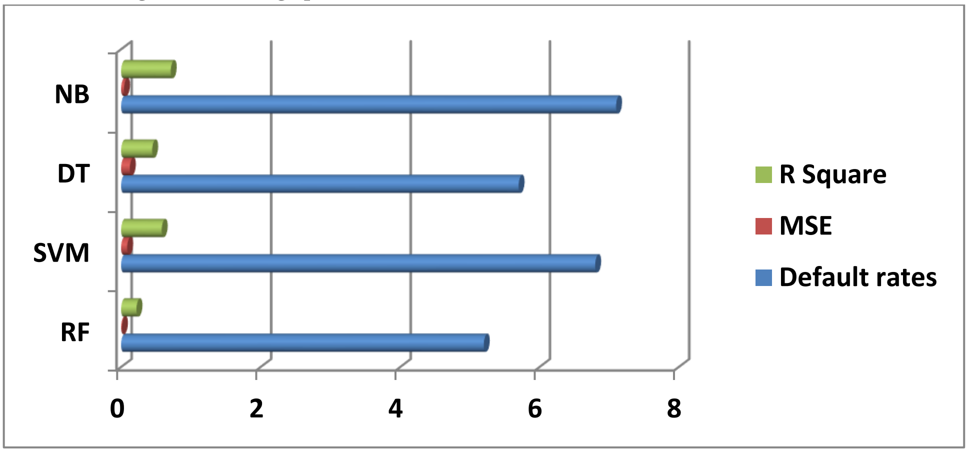

Fig 3: Comparison of MSE , R Square of different model

In the context of credit scoring, Table 4 provides a thorough review of the performance measures for four different machine learning algorithms. These metrics Recall, Precision, F1 Score, and Area Under the Curve (AUC) act as important yardsticks for assessing each algorithm's efficacy.

Table 4: Summary of performance metrics

Algorithm	Recall	Precision	F1 Score	AUC
Random Forest	0.85	0.90	0.87	0.92
Naive Bayes	0.72	0.78	0.75	0.80
Support Vector	0.88	0.86	0.87	0.89
Decision Tree	0.80	0.82	0.81	0.85

With a Recall of 0.85, Random Forest stands out because it can reliably detect a significant number of true positive situations. This is coupled with high Precision (0.90), highlighting its skill in reducing false positives. The ensuing Precision/Recall trade-off is well-balanced, as seen by the F1 Score of 0.87. Its AUC of 0.92 also indicates great discrimination between favourable and unfavourable credit outcomes.With a Recall of 0.88 and an outstanding Precision of 0.86, Support Vector Machine (SVM) also performs admirably. An F1 Score of 0.87 is obtained as a result of this combination, indicating that true positives and false positives are distributed favourably. With an AUC of 0.89, SVM still performs admirably despite not matching Random Forest's AUC.

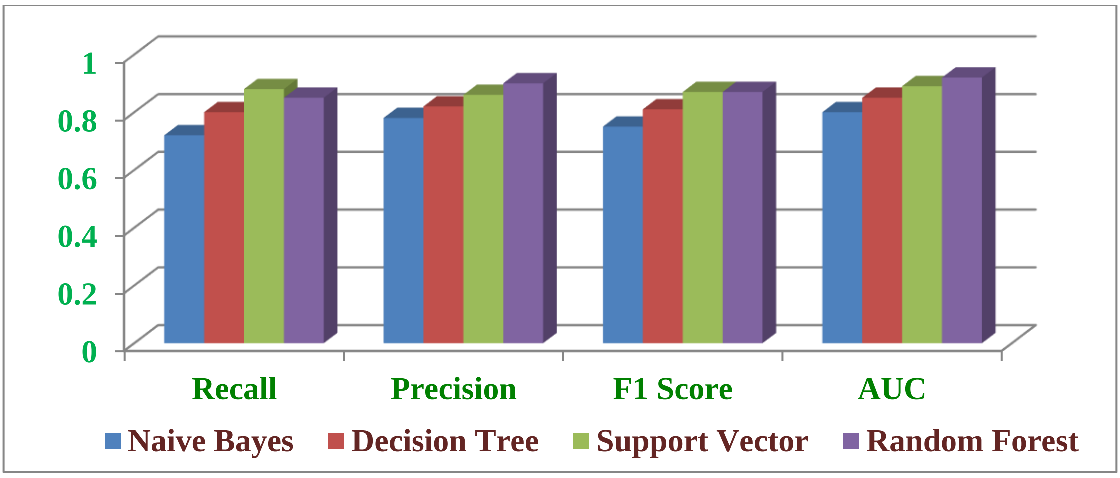

Fig 4: representation of performance metrics for proposedML model

Fig 5: Model Accuracy Comparison

Both Decision Tree and Naive Bayes (NB) work admirably. With an F1 Score of 0.75 and an AUC of 0.80, Naive Bayes maintains a reasonable Recall of 0.72 and Precision of 0.78. Decision Tree obtains an F1 Score of 0.81 and an AUC of 0.85 with a Recall of 0.80 and Precision of 0.82.As a result of their balanced Recall, Precision, F1 Score, and AUC values, Random Forest and SVM stand out as the top performers. These models are intriguing options for precise credit scoring since they are excellent at correctly identifying positive credit outcomes while successfully minimising false positives. Therefore, it is advised to use Random Forest and SVM for situations where accurate credit scoring is essential.

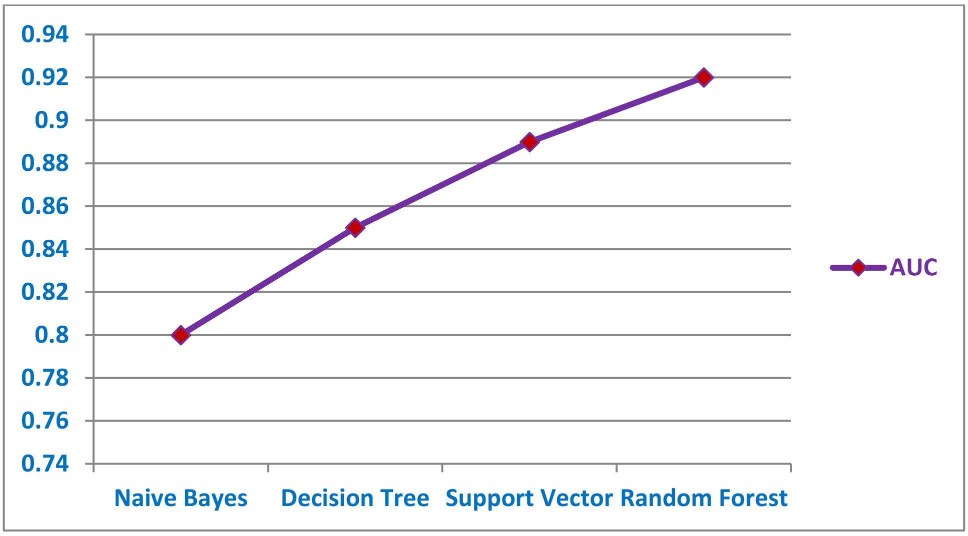

Fig 6: Model AUC Comparison for proposed methods

VI. Conclusion

The outcomes of these models offer insightful information. With remarkable accuracy, low default rates, and outstanding performance in terms of Mean Squared Error (MSE) and R-squared values, Random Forest emerges as the clear winner. Following closely, SVM displays significant R-squared values that indicate its aptitude for capturing and elucidating dataset volatility. Financial institutions can greatly benefit from these findings as they work to reduce risk and improve lending decisions.The power of Random Forest and SVM is further enhanced by a thorough analysis of performance indicators. Recall, Precision, F1 Score, and Area Under the Curve (AUC) metrics for these models show a pleasing balance, demonstrating their balanced ability to identify creditworthy people while minimising false positives.Though they fall short of Random Forest and SVM in terms of credit rating, Naive Bayes and Decision Tree nevertheless produce decent outcomes, therefore it is important to recognise their potential.These cutting-edge machine learning approaches represent a quantum leap ahead in the fast changing financial sector where accurate credit assessment is essential for responsible lending. They enable financial organisations to make profitable decisions, lower default rates, and ultimately promote economic stability by improving accuracy and risk assessment capabilities.

References

[1] Malekipirbazari, MiladAksakalli, Vural. (2015). Risk Assessment in Social Lending via Random Forests.Expert Systems with Applications.10.1016/j.eswa.2015.02.001.

[2] Ahelegbey, D. F., Giudici, P., and Hadji-Misheva, B. (2019a).Factorial Network Models to Improve P2p Credit Risk Management.Front.Artif.Intell.2

[3] GramespacherTandPosthJ-A (2021) Employing Explainable AI to Optimize the Return Target Function of a Loan Portfolio. Front. Artif. Intell. 4:693022.

[4] https://www.lendingclub.com/ [12] Aniceto, Maisa Cardoso et al. "Machine learning predictivity applied to consumer creditworthiness." Future Business Journal vol. 6,1(2020): 37.

[5] H. Markowitz, "Portfolio selection," e Journal of Finance, vol. 7, no. 1, pp. 77–91, 1952. [14] H. M. Markowitz, Portfolio Selection: Efficient Diversification of Investment, Wiley, New York, NY, USA, 1959.

[6] Serrano-Cinca, CarlosGuti´errez-Nieto, Begon˜aL´opez-Palacios, Luz. (2015). Determinants of Default in P2P Lending. PLOS ONE. 10.e0139427.10.1371/journal.pone.0139427.

[7] Óskarsdóttir, C. Bravo, C. Sarraute, J. Vanthienen, and B. Baesens, "The value of big data for credit scoring: enhancing financial inclusion using mobile phone data and social network analytics," Applied Soft Computing, vol. 74, pp. 26–39, 2019.

[8] S. S. Luvizan, P. T. Nascimento, and A. Yu, "Big data for innovation: the case of credit evaluation using mobile data analyzed by innovation ecosystem lens," in Proceedings of the 2016 Portland International Conference on Management of Engineering and Technology (PICMET), pp. 925–936, Honolulu, HI, USA, September 2016.

[9] W. Wang, C. Lesner, A. Ran, M. Rukonic, J. Xue, and E. Shiu, "Using small business banking data for explainable credit risk scoring," Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 8, pp. 13396–13401, 2020.

[10] V. Kuppili, D. Tripathi, and D. R. Edla, "Credit score classification using spiking extreme learning machine," Computational Intelligence, vol. 36, no. 2, pp. 402–426, 2020.

[11] N. Jain, T. Agrawal, P. Goyal, and V. Hassija, "A blockchain-based distributed network for secure credit scoring," in Proceedings of the 2019 5th International Conference on Signal Processing, Computing and Control (ISPCC), pp. 306–312, IEEE, Solan, India, October 2020.

[12] C. Wang, D. Han, Q. Liu, and S. Luo, "A deep learning approach for credit scoring of peer-to-peer lending using attention mechanism LSTM," IEEE Access, vol. 7, no. 99, p. 1, 2018.

[13] D. Chen, F. Lai, and Z. Lin, "A trust model for online peer-to-peer lending: a lender's perspective," Information Technology and Management, vol. 15, no. 4, pp. 239–254, 2014.

[14] S. Ajani and M. Wanjari, "An Efficient Approach for Clustering Uncertain Data Mining Based on Hash Indexing and Voronoi Clustering," 2013 5th International Conference and Computational Intelligence and Communication Networks, 2013, pp. 486-490, doi: 10.1109/CICN.2013.106.

[15] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[16] Potnurwar, A. V. ., Bongirwar, V. K. ., Ajani, S. ., Shelke, N. ., Dhone, M. ., & Parati, N. . (2023). Deep Learning-Based Rule-Based Feature Selection for Intrusion Detection in Industrial Internet of Things Networks. International Journal of Intelligent Systems and Applications in Engineering, 11(10s), 23–35.

[17] A. Ashofteh and J. M. Bravo, "A conservative approach for online credit scoring," Expert Systems with Applications, vol. 176, p. 114835, 2021.

[18] J. Wu, Q. Zhang, Y. Zhao et al., "Radiomics analysis of iodine-based material decomposition images with dual-energy computed tomography imaging for preoperatively predicting microsatellite instability status in colorectal cancer," Frontiers in oncology, vol. 9, p. 1250, 2019.

[19] Z. Gao, L. Ding, Q. Xiong, Z. Gong, and C. Xiong, "Image compressive sensing reconstruction based on z-score Standardized group sparse representation," IEEE Access, vol. 7, no. 99, p. 1, 2019.

[20] L. Yuanqing, Y. Suying, X. Jiangtao, and G. Jing, "A self-checking approach for SEU/MBUs-hardened FSMs design based on the replication of one-hot code," IEEE Transactions on Nuclear Science, vol. 59, no. 5, pp. 2572–2579, 2012.

[21] J. Li, L. Ren, B. Wang, and G. Li, "Probabilistic load forecasting of adaptive multiple polynomial regression considering temperature scenario and dummy variables," Journal of Physics: Conference Series, vol. 1550, no. 3, pp. 1–16, 2020.

[22] L. Teng, H. Li, S. Yin, and Y. Sun, "A new chi-square distribution de-noising method for image encryption," International Journal on Network Security, vol. 21, no. 5, pp. 804–811, 2019.

[23] G. Chen, Q. Pei, and M. M. Kamruzzaman, "Remote sensing image quality evaluation based on deep support value learning networks," Signal Processing: Image Communication, vol. 83, p. 115783, 2020.

[24] G. Chen, X. Xie, and S. Li, "Research on complex classification algorithm of breast cancer chip based on SVM-RFE gene feature screening," Complexity, vol. 2020, Article ID 1342874, 12 pages, 2020.

[25] M. C. Tsai, S. P. Lin, C. C. Cheng and Y. P. Lin, "The consumer loan default predicting model - An application of DEA-DA and neural network", Expert Systems with Applications, vol. 36, no. 9, pp. 11682-11690, 2009.

[26] K. Tsai, S. Ramiah and S. Singh, "Peer Lending Risk Predictor", Stanford University CS229 Project Report, 2014.

[27] S. Akkoc, An empirical comparison of conventional techniques neural networks and the three stage hybrid Adaptive Neuro Fuzzy Inference System (ANFIS)model for credit scoring analysis: The case of Turkish credit card data. European Journal of Operational Research, vol. 222, no. 1, pp. 168-178, 2012.

[28] M. Herzenstein, U. M. Dholakia and R. L. Andrews, "Strategic herding behavior in Peer-to-Peer loan auctions", Journal of Interactive Marketing, vol. 25, no. 1, pp. 27-36, 2011.

[29] D. Zhang, H. Huang, Q. Chen and Y. Jiang, "A comparison study of credit scoring models", Proceedings - Third International Conference on Natural Computation, vol. 1, pp. 15-18, 2007.

[30] S. S. D.-o. Kim Chang and G. Kondo, "Predicting default risk of lending club loans", Machine Learning, pp. 1-5, 2015.

[31] M. Malekipirbazari and V. Aksakalli, "Risk assessment in social lending via random forests", Expert Systems with Applications, vol. 42, no. 10, pp. 4621-4631, 2015