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Corporate Credit Rating Prediction Using Explainable AI

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Abstract:
Credit ratings are independent opinions expressed by rating agencies on a company's risk profile and future financial commitments. Artificial intelligence (AI) has become increasingly popular for credit assessment, with neural networks and support vector machines offering superior accuracy. This paper analyzes datasets from seven US-based industrial sectors and uses a hybrid ensemble learning model using six machine learning models, including Random Forest, Naïve Bayes, k-Nearest Neighbors, Decision Tree, Support Vector Machine, and Logistic Regression to distinguish between investment and non-investment grades. The hybrid model works best for the DURABLES sector, followed by TELECOM and HEALTH sectors. Explainable AI (XAI) tools like LIME and SHAP explain the prediction outcome of investment-grade and non-investment-grade credit ratings classification. The paper also compares the performance of the hybrid model with eight other related datasets for assessing credit ratings.

Keywords: *Artificial Intelligence, Corporate Credit Rating, Explainable AI, Hybrid Ensemble, Investment Grade, LIME, Non-investment Grade, PRISMA, SHAP*

1 Introduction

The Indian industrial sector's rapid growth has necessitated the development of financial markets to raise capital. Credit rating agencies, like ICRA, CRISIL provide independent opinions on a company's ability to meet debt obligations promptly. A favorable credit rating attracts new investors and reduces capital costs. Investors value the return on shares, and rating changes can affect these returns. This study aims to develop a credit rating prediction model using Artificial Intelligence (AI) to predict sector-wise credit ratings for various sectors, including shops, telecommunication, business equipment, durables, health, and energy. The results are explained using eXplainable AI (XAI) (G. P. Reddy & Kumar, 2023).

AI, a technology that models human cognition in computers, is revolutionizing industries like finance by boosting output, reducing costs, and improving decision-making, particularly in the financial sector. Using data from 68 Credit Managers from Financial Services Provider firms, research examines the effects of integrating AI into financial institutions' operations to generate credit scores for lending. It recommends that financial institutions take cost-cutting measures, upgrading skills, and protecting client privacy to enable FinTech companies to better build their products and use AI more effectively to connect with more potential clients and offer better services (Dhaigude & Lawande, 2022). AI algorithms analyze data for accurate risk assessments, fraud detection, and personalized customer support, while robo-advisors generate automated investment advice, increasing accessibility and lowering financial planning costs. (Day et al., 2018). AI-powered algorithms optimize trading strategies, improve investing outcomes, and enhance loan underwriting. They improve communication between financial institutions and clients, and aid in predictive analytics for market forecasting, enabling informed financial judgments. Natural language processing (NLP) has made it possible for AI to read and respond to written or spoken language, enhancing communication between financial institutions and their clients (Savadatti et al., 2022). AI is transforming the finance sector, bringing about improvements in efficiency, security, and client focus.

Credit rating agencies are increasingly utilizing artificial intelligence (AI) to improve their credit rating processes. AI algorithms analyze large datasets, providing more accurate and efficient creditworthiness evaluations. AI also helps predict default risks and identify potential credit fraud. Machine learning (ML) in AI focuses on developing statistical models and algorithms that enable computers to improve their proficiency over time without explicit guidance. (Rao et al, 2022). ML algorithms, including unsupervised and supervised learning, are essential in sectors like marketing, healthcare, and finance for identifying trends, making inferences, and predicting future events.
Unsupervised learning is an algorithm that learns from unlabelled data without target labels to explore patterns or structure. It is often used for dimensionality reduction and clustering, using methods like Hierarchical Clustering and Principal Component Analysis. Supervised learning, on the other hand, uses labelled data to make predictions, with methods like

random forests, decision trees, neural networks, and SVM. Hybrid ensemble machine learning models combine ensemble learning principles with supervised and unsupervised machine learning techniques to improve prediction performance. (Jin et al., 2021). Ensemble learning involves combining multiple models to produce superior outcomes, often through weighted voting or averaging forecasts. Hybrid ensemble models, which incorporate multiple models or algorithms, improve performance, resilience, and generalization, especially for complex datasets or when no efficient solution exists.

A subfield of artificial intelligence called XAI aims to improve machine learning models' comprehensibility and transparency (Barredo Arrieta et al., 2020). XAI techniques aim to enhance transparency in decision-making processes, particularly in complex problems. They include rule extraction, model visualization, and feature significance analysis, crucial in fields like healthcare, banking, and criminal justice. Researchers are developing XAI approaches to create accountable, transparent, and human-friendly AI systems.(Y.W. Chen et al., 2023).

XAI's focus on unlocking black-box models enhances model explainability, enabling investors to understand credit rating forecasts and ensuring stakeholder rights under GDPR's "right to explanation" for company information."(Freitas et al., 2023) Therefore, for corporate credit rating agencies across several industrial sectors to implement credit rating models, they must be both optimal classifiers and interpretable.

1.1 Contribution

The key contributions to this paper are as follows.

1. Conduction of AI-based credit rating forecasts using a systematic literature review (SLR) by adopting the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach,
2. Creation of a hybrid ensemble supervised machine learning model to forecast investment grade and non-investment grade credit ratings using an US-based corporate credit rating dataset sourced from Kaggle that includes information on seven different industry sectors, such as shops, telecommunication, business equipment, durable goods, health, energy, and other.
3. Interpretation and explanation of the outcomes in step 2 utilizing Local Interpretable Model Agnostic Explanation (LIME) and SHapley Additive exPlanations (SHAP) for the local and global explanations of the significant features involved in the prediction, respectively.

1.2 Organization

This is how the remainder of the paper is structured. Section 2 describes SLR using the PRISMA model while Section 3 enumerates related papers. Section 4 presents the hybrid ensemble model for credit rating prediction, which includes the system architecture and model, datasets for investment grade and non-investment grade credit rating categorization, and exploratory data analysis for feature extraction. The simulation and performance analysis of the suggested model are shown in Section 5. A performance comparison with similar studies is provided in section 6. Section 7 provides a summary of the paper's conclusions regarding its future direction and scope.

2 Systematic Literature Review (SLR)

To conduct SLR in the current corpus of research, we use PRISMA (Selcuk, 2019), an evidence-based minimal collection of questions for reporting in systematic reviews and meta-analyses (Hinderks et al., 2020). Although PRISMA is largely focused on the reporting of reviews of randomized trials, it can also be used as a basis for conducting systematic reviews of other forms of research, such as treatments (Pahlevan Sharif et al., 2019).

2.1 Methodology

There are four steps of SLR (Kumar, 2023), which are explained below.

2.1.1 Research topic

Defining the study topic and creating a thorough search strategy based on keywords and inclusion and exclusion criteria are the first steps in the process.

2.1.2 Resource identification

The study evaluates 105 papers from industry whitepapers and scholarly journals between 2004 and 2022 using inclusion and exclusion criteria. It assesses titles and abstracts, focusing on advantages, disadvantages, methods, study setting, and relationships. The search strategy considers parameters like credit rating, investment grade, return on investment, net profit, and artificial intelligence.

2.1.3 Data collection and analysis

The third phase is gathering information on subjects, interventions, outcomes, and sample size from every study using a uniform form. Studies published between 2004 and 2022, peer-reviewed articles, publishing in reputable English-speaking journals, and conference proceedings were the three criteria used to restrict the study.

2.1.4 Data synthesis

The fourth phase entails synthesizing the findings of the chosen studies, depending on the research topic and the study methodology. At this point, a qualitative or statistical synthesis might be necessary. Building the data analysis flow diagram, as shown in The PRISMA paradigm (Rethlefsen et al., 2021) served as the foundation for Figure 1. The figure illustrates that a total of 105 papers were found by utilizing the pertinent keywords. After a preliminary search to determine eligibility, 84 papers were found to be eligible. Using online software, sixteen duplicates were eliminated, leaving 68 publications suitable for full-text scanning. The irrelevant content of twenty-two articles led to their deletion. 14 publications that had nothing to do with the inquiry were removed, leaving 46 papers that still require review and analysis. For additional review in order to conduct a qualitative and quantitative synthesis, 32 publications were selected. These numbers are represented by 'var'.

Identification	Articles identified through database searching {var = 102; using IEEE Xplore (17), Taylor & Francis (3), SpringerLink (36); Web of Science (8), Google Scholar (5), Science Direct (6), SCI (3), Google (15), SSRN (4), ResearchGate (2), Sage (1), Emerald (2)}	Additional articles identified through other sources (var = 3)
	Total articles retrieved (var = 105) Articles excluded based on title and abstract (var = 21)	
Screening	Articles screened for duplicates (var = 84)	Duplicates removed (var = 16)
Eligibility Iteration	Articles screened Full-text scanning (var = 68)	Full-text articles excluded, irrelevant (var = 22)
	Articles screened Full-text analysis and evaluation (var = 46)	Full-text articles omitted, not directly related (var = 14)
Inclusion	Studies included in qualitative and quantitative synthesis (var = 32)	

Fig. 1 PRISMA Flow Diagram

3 Related works

This section intricately discusses the previous works in the area of credit rating affecting stock market prices, stock liquidity, and AI-based credit rating models.

3.1 Impact of Credit Rating on Stock Prices

The event study methodology has been employed in numerous research to examine the effects of changes in credit ratings on stock prices. (Raghunathan & Choy, 2006) investigated the impact of Standard & Poor's and Moody's rating changes on Australian company stock returns. The study found that the most noticeable stock price response is observed when a downgrade is unexpected, unregulated, and the rating drops by multiple categories. (Lal & Mitra, 2011) in their study from 2002 to 2008 examined the impact of bond rating changes on equity share prices in India, analysing 117 long-term debt instruments from 98 companies using event study methodology. The findings revealed an information leakage to the investment community about company's financial performance even before the ratings were changed publicly.(Poornima et al , 2015)'s study from 2010-2014 found that credit rating changes significantly impacted share prices of 12 mid-capitalized and 12 small-capitalized Indian companies listed on the Bombay Stock Exchange, with downgrades having a more significant impact, especially near announcement dates.(Jaworska, 2016) The article analyzes how credit rating changes affect bank share returns across 25 countries from 1980 to 2015. The study uses event study methods and daily differences between logaritmized share returns to conclude that in both developed and developing economies the most prominent impact of credit rating changes is observed for downgrades. (Miyamoto, 2016) The study investigates Japanese companies' reactions to credit ratings to debt, using event study methodology and Tokyo Stock Price Index returns. Results show that negative announcements from Japanese companies lead to positive market reactions, and stock prices respond even before rating changes are announced. (Gupta, 2017) The study examined the impact of downgrades on a bank's stock market price, using an event study methodology, 45 days before and after rating change announcements. The study revealed that the returns of the banking stock were impacted more by downgrades. (Tripathy, 2017) The paper uses event study methodology to analyze the impact of rating change announcements on Indian stock markets, revealing that downgrades and upgrades have positive and statistically insignificant AARs, and credit rating announcements only summarize publicly available information. (Pinto, 2018) The study examined the impact of rating releases on Brazilian firms listed on BOVESPA between 2002 and 2018, using Excel's Capital Asset Pricing Model to analyze abnormal returns before and after credit rating announcements.(Rafay et al., 2018) found that credit ratings significantly impact stock prices in Taiwanese firms from 2010-2015, supporting signalling theory and influencing investors' buying and selling decisions. (D. Reddy et al., 2019) in their study from 2006-2015 found that credit rating changes significantly impacted stock prices of American firms listed on Standard & Poor's 500, with downgrades causing more significant reactions than improvements.(Xie et al., 2019) studied the effect of credit rating announcements on stock returns of 32 Pakistani business organizations found a significant positive impact on returns with an upgrade and a negative abnormal return with a downgrade. (Dawar et al., 2021) The study examined the impact of credit rating changes on the share prices of 100 Indian companies listed on the National Stock Exchange from 2009 to 2019. Results showed that the event effect was more prominent in the pre-event phase and the effect of downgrades are statistically significant than upgrades. (Even-Tov & Ozel, 2021) observed a downgrade of credit rating often divulge new information that led to changes in price of stock rather than upgrades. Rating agencies delay public announcements to enable issuers to respond and engage in informed trading. Rating modification reports from Fitch, S&P, and Moody's show that stock prices respond better to long-term issuer ratings than individual instrument ratings. In their research, (Pagin et al., 2021) The study investigates the impact of upgrades and downgrades on Brazilian firms' stock returns from 2002-2018. It found that accumulated abnormal returns increase before upgrades and decrease post-downgrades. The study suggests that rating changes impact stock prices, and market reactions can be anticipated.

3.2 Impact of Credit Rating on Stock Liquidity

Credit rating changes significantly impact stock prices, but their impact on stock liquidity is less studied, especially in India, despite extensive literature review. (Robles-Fernández, 2012) found that rating announcements significantly impact trading activity in Spanish commercial papers and corporate bond markets, increasing yield spread and trading frequency. A decline in trade volumes following downgrades were also observed. (Feda, n.d.) examines the relationship between credit ratings and firms' capital structure from 2008 to 2017. It found that downgraded firms reduce debt and issue equity to reduce risk, potentially increasing equity trading volume. The dataset includes New York Stock Exchange firms.(Saadaoui et al., 2022) examines how credit ratings from rating organizations impact bond liquidity, analyzing data from over 140 bonds from 2009 to 2017. Fitch's credit ratings were approved, and ratings adjustments have been shown to affect bond prices, trade, and liquidity.

3.3 AI-based Credit Rating Models

(Golbayani et al., 2020) compares four ML approaches using data from four algorithms: Multilayer Perceptron, Random Forest (RF), Support Vector Machine (SVM), and Bagged Decision Trees, revealing decision tree-based models perform better and providing a notch-based accuracy metric. (Sadok et al., 2022) explores the use of AI in credit analysis by banks and financial organizations, highlighting its potential to improve macroeconomic projections and financial inclusion for marginalized borrowers. (Dhaigude & Lawande, 2022) examines the impact of AI on financial institutions' credit scores generation, suggesting cost-cutting measures for FinTech companies to enhance product development and service delivery. (Pol et al., 2022) uses Deep-Learning models to automate credit ratings in India's IT sector, revealing that Machine Learning and AI can enhance credit risk assessments and loan acceptability. (Alonso & Carbó, 2021) compares various machine learning models, including Lasso penalized logistic regression, Classification and Regression Tree, RF, XGBoost, and Deep Neural Networks, to predict credit default. (Bussmann et al., 2021) proposes an AI model for credit risk management in peer-to-peer lending networks, utilizing Shapley values and TreeSHAP to predict default chances and improve understanding of financial risk factors. (Khemakhem, 2018) explores the use of AI algorithms like Artificial Neural Network (ANN), SVM, and Logistic Regression (LR) to estimate credit risk in Tunisian loan applications. (Misheva et al, 2021) utilizes SHAP and LIME to enhance machine learning-based credit scoring models on an open-access data set from Lending Club, a US P2P lending platform. (Raaij, 2025) uses AI in individual risk assessment across European mortgage and credit card markets, showing it outperforms conventional models, suggesting scalable automated credit risk solutions. (Xu et al., 2019) develops a user-friendly tool for evaluating seller credit risk using hybrid AI models, with the decision tree-ANN combination providing optimal accuracy.

(Huang et al., 2004) investigates the use of AI techniques in corporate credit ratings analysis, achieving 80% prediction accuracy and improving interpretability, focusing on financial variables. (Hwang et al., 2010) introduces a credit risk prediction method using an ordered semiparametric probit model, allowing for flexible selection and comparing it with the standard probit model using real data. (Kim & Ahn, 2012) introduces a novel classifier type, OMSVM, which efficiently handles multiple ordinal classes and requires less processing power than traditional MSVM methods. (Chen & Chen, 2022) focuses on predicting corporate credit ratings using social media sentiment, revealing that K-Nearest Neighbour (k-NN) model outperforms traditional financial reports and macroeconomic indicators. (Ubarhande & Chandani, 2021) encourages the development of a sector-specific credit-rating system using advanced techniques and offers a study program to explore credit-rating topics and creditworthiness criteria across sectors.

1.4 Observations

Credit rating changes significantly impact stock prices in both developing and developed economies, particularly near announcement dates. Downgrades are more intense when rating shifts from investment-grade to non-investment-grade firms, while upgrades have a severe effect when it is from noninvestment grade to investment grade. Stock prices react more before announcements, with long-term issuer ratings having a prominent effect on downgrades.

4 Proposed Work

This section describes the suggested corporate credit rating model. This covers the architecture and system model, the datasets used to classify data as investment-grade or non-investment-grade, and the exploratory data analysis done to extract features from the data.

4.1 System Model

This section contains the system model for the suggested corporate credit rating model that uses XAI. The recommended system model's architecture is depicted in Figure 2. It is separated into three main sections, which are called Segments A, B, and C.

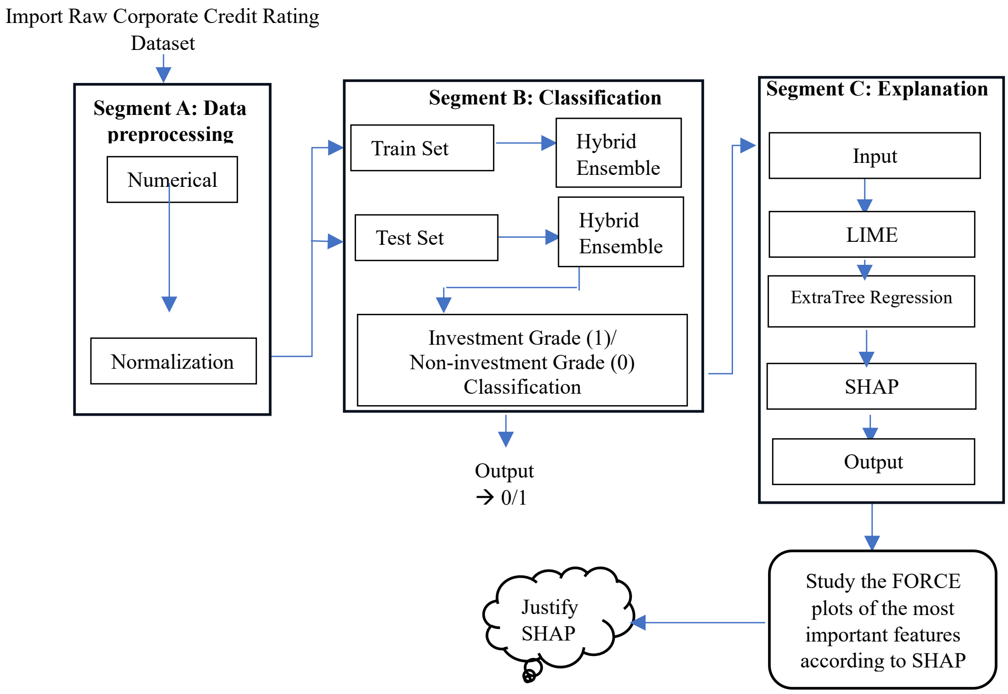

Fig. 2 Architecture of the Proposed Credit Rating Prediction Model

The data preparation modules are in Segment A; the credit rating investment and non-investment grade classification jobs are in Segment B; and the explanation modules are in Segment C. Preprocessing data is crucial for reducing noise in machine learning models. It involves transforming the dataset into numerical form, normalizing it, and standardized using feature scaling. Regularization and normalization are techniques used to standardize variables and features, ensuring accurate and effective models with varied scales or no outliers.

(Cabello-Solorzano et al., 2023).Since the dataset utilized in this investigation has varying scales, normalization is necessary. The normalization formula is given by Eq (1):

$$Xnew = (Xi - Xmin) / (Xmax - Xmin) \qquad (1)$$

where Xi is the existing feature vector, Xmin is the minimum value of that feature vector, and Xmax is its maximum value.

The pre-processed dataset in the classification component is divided into two parts. The remaining 75% of the dataset is utilized to train the model, and the remaining 25% is used for testing and validation using a hybrid approach that includes five ensemble machine-learning techniques. The explanation section uses the SHAP (Zhang et al., 2024) algorithm for global explanations and the LIME (Aljadani et al., 2023)method for local explanations to ensure model interpretability (Shah et al., 2024). The predictions of the ML model make sense given its local character. In this instance, the explanation is based on a single event from the test data. By assessing the importance of each attribute to the prediction, the SHAP technique seeks to explain the anticipated outcome of a specific case or observation. The outcomes of the credit rating grade classification are backed up by an analysis of the force plots of the key SHAP properties.

4.2 Datasets

The text explains the concept of data points, feature vectors, and targets in seven dataset sectors. The target is the output variable influenced by the feature vectors, while a data point describes a single observation unit.

- *Sectors:* Corporate credit ratings of seven different sectors have been identified to serve the purpose of this research. These sectors are
  - i) SHOPS - Retail companies that sell consumer items, such as apparel, electronics, and home goods, through physical storefronts or online platforms.
  - ii) Telecommunication (TELCM) – Businesses that offer consumers and businesses communication services like phone, internet, and television services.

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iii) Business Equipment (BUSEQ) - The business equipment sector encompasses the sale, lease, installation, and servicing of various types of equipment used in business settings such as computers, data processors, photocopiers, FAX, calculators, etc.
iv) Durables (DURBL) – Companies that manufacture furniture, appliances, and cars—items meant to survive for a long time.
v) Healthcare (HLTH) – The healthcare sector encompasses businesses that provide healthcare services and goods, including hospitals, pharmaceutical companies, and makers of medical equipment.
vi) Energy (ENRGY) – Businesses engaged in the production, sale, and distribution of products that are energy sources such as electricity, gas, and oil.
vii) Other Industries (OTHER) – In addition to the above industries, several other industries are aggregated as other industries.

- *Features:* The fifteen extracted features, specifications, and descriptions are presented in Table 1B.
- *Target:* Investment grade or non-investment grade
- *Datapoints:*

i) The SHOPS dataset comprises 455 data points.
ii) The TELCM dataset comprises 290 data points.
iii) The BUSEQ dataset comprises 644 data points.
iv) The DURBL dataset comprises 130 data points.
v) The HLTH dataset comprises 378 data points.
vi) The ENRGY dataset comprises 427 data points.
vii) The OTHER dataset comprises 644 data points

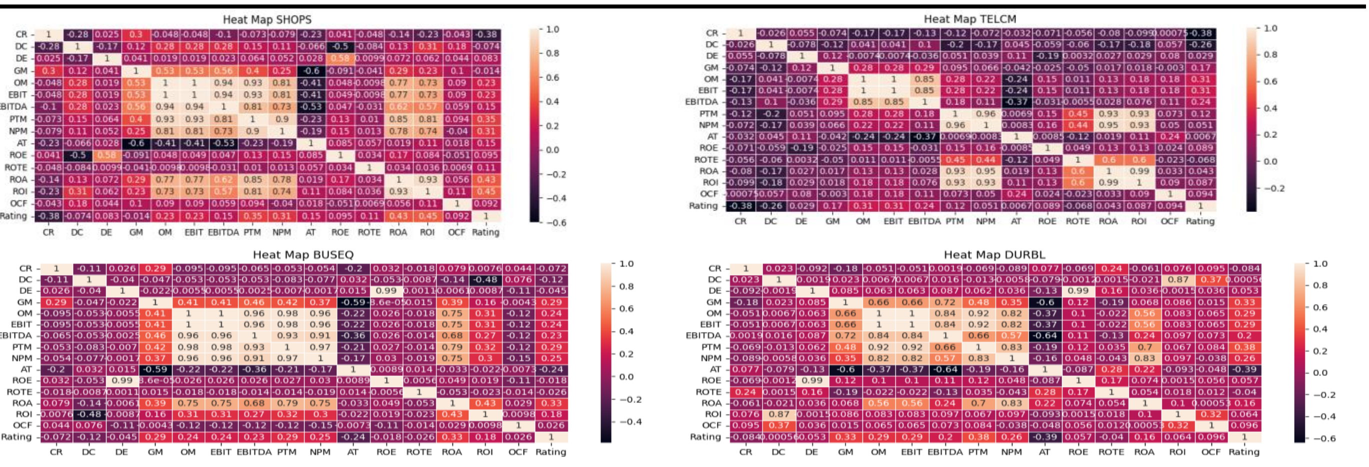
5. Simulation and Performance Analysis

Python is the computer language used to simulate the three segments of Figure 3.

5.1 Segment A: Data Preprocessing

Exploratory Data Analysis (EDA) is a crucial phase in data analysis, aiding in understanding data distribution and features (Rao et al., 2021). It uses methods like dimensionality reduction, data visualization, and summary statistics to identify patterns, abnormalities, and test theories. EDA can be univariate, bivariate, or multivariate, and visualization tools like plots, charts, and graphs help spot trends (*Exploratory Data Analysis BT - The Concise Encyclopedia of Statistics*, 2008).

This project used Python as an EDA tool, focusing on data dimension, classes, predictor and label distribution, missing values, and outliers. Python's dynamic typing and built-in data structures make it ideal for creating applications and connecting pre-existing components. Heat maps and correlation matrices were used. The heat maps of the seven datasets that are being examined are displayed in Figure 3. Correlated feature vectors with values greater than or equal to ±0.1 were retained in the analysis, whereas those with values less than or equal to ±0.1 were eliminated, as Table 1A illustrates. In Table 1A and Figure 3, the features EBIT and EBITDA indicate EBIT margin and EBITDA margin respectively. According to the correlation matrices, fifteen features were retrieved, as the table shows. Table 1B shows the specifications with expressions Eq (2) - Eq (16) and descriptions of the features that were extracted. The two types of grades were classified as investment (1) and non-investment (0) using the attributes that were retrieved.



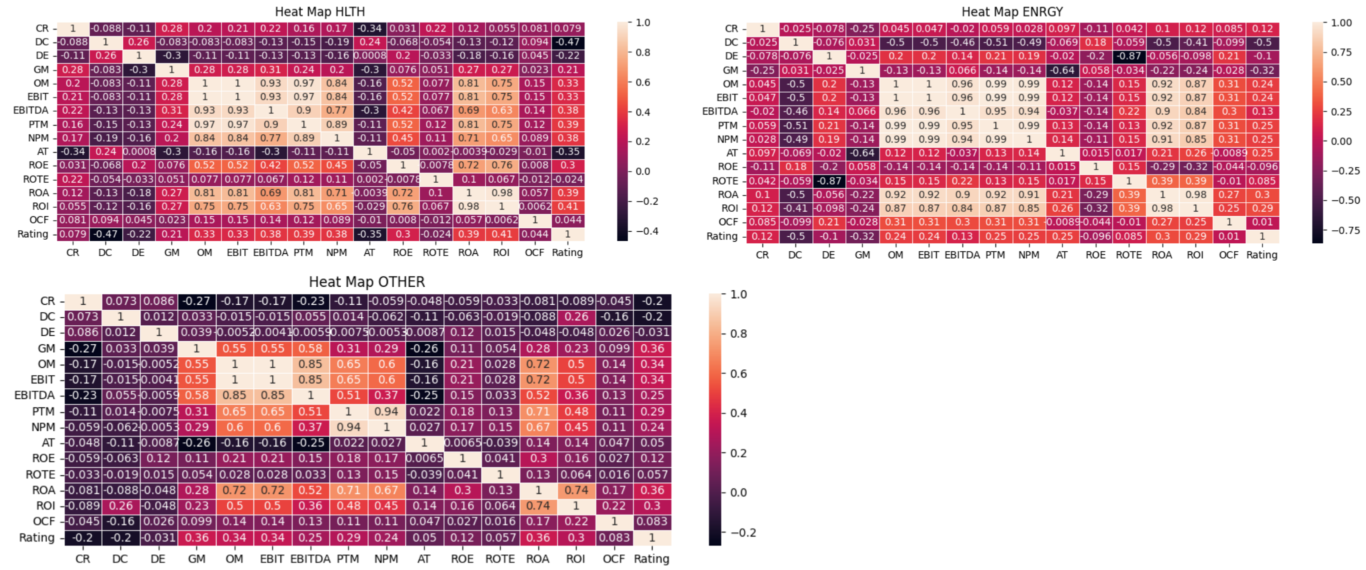


Fig. 3 Heat Map (Correlation Matrix) of Seven Sectors

Table 1A Feature Extraction of Corporate Credit Rating Datasets of Different Sectors

	Sector	SHOPS		TELCM		BUSEQ		DURBL	
Sl. No.	Extracted Feature	Quality	Status	Quality	Status	Quality	Status	Quality	Status
0	CR	-0.38	include	-0.38	include	-0.072	drop	0.084	drop
1	DC	-0.074	drop	-0.26	include	-0.12	include	0.0005	drop
2	DE	0.083	drop	0.029	drop	-0.045	drop	0.053	drop
3	GM	-0.014	drop	0.17	include	0.29	include	0.33	include
4	OM	0.23	include	0.31	include	0.24	include	0.29	include
5	EBIT	0.23	include	0.31	include	0.24	include	0.29	include
6	EBITDA	0.15	include	0.24	include	0.23	include	0.2	include
7	PTM	0.35	include	0.12	include	0.29	include	0.38	include
8	NPM	0.31	include	0.051	drop	0.25	include	0.26	include
9	AT	0.15	include	0.0067	drop	-0.24	include	-0.39	include
10	ROE	0.095	drop	0.089	drop	-0.018	drop	0.057	drop
11	ROTE	0.11	include	-0.068	drop	-0.026	drop	-0.04	drop
12	ROA	0.43	include	0.043	drop	0.33	include	0.16	include
13	ROI	0.45	include	0.087	drop	0.18	include	0.064	drop
14	OCF	0.092	drop	0.094	drop	0.026	drop	0.096	drop

	Sector	HLTH		ENRGY		OTHER	
Sl. No.	Extracted Feature	Quality	Status	Quality	Status	Quality	Status
0	CR	0.079	drop	0.12	include	-0.2	Include
1	DC	-0.47	include	-0.5	include	-0.2	Include
2	DE	-0.22	include	-0.1	include	-0.031	Drop
3	GM	0.21	include	-0.32	include	0.36	Include
4	OM	0.33	include	0.24	include	0.34	Include
5	EBIT	0.33	include	0.24	include	0.34	Include

6	EBITDA	0.38	include	0.13	include	0.25	Include
7	PTM	0.39	include	0.25	include	0.29	Include
8	NPM	0.38	include	0.25	include	0.24	Include
9	AT	-0.35	include	0.25	include	0.05	Drop
10	ROE	0.3	include	-0.096	drop	0.12	Include
11	ROTE	-0.024	drop	0.085	drop	0.057	Drop
12	ROA	0.39	include	0.3	include	0.36	Include
13	ROI	0.41	include	0.29	include	0.3	Include
14	OCF	0.044	drop	0.01	drop	0.083	Drop

Table 1B Specifications of the Extracted Features of Corporate Credit Rating Dataset

Feature No.	Extracted Features	Specifications
0	Current ratio (CR)	CR = Current assets/ Current liabilities (2)
1	Debt to Capital Employed Ratio (DC)	DC = Debt/ (debt + Shareholder's equity) (3)
2	Debt-Equity Ratio (DE)	DE = (Short term debt + Long term debt)/ (Share capital + Reserves) (4)
3	Gross Margin (GM)	GM = (Gross profit /Sales) x 100 (5)
4	Operating Margin (OM)	OM = (Operating Profit/sales) x 100 (6)
5	Earnings before Interest and Tax (EBIT) Margin	EBIT = Total Sales – COGS – Operating Expense = Gross Profit - Operating Expense Where COGS = Cost of Goods Sold EBIT Margin = ((Total sales-COGS-Operating expense) /Sales) x 100 (7)
6	Earnings before Interest, Tax, Depreciation, and Amortisation (EBITDA) Margin	EBITDA = EBIT + Depreciation + Amortisation EBITDA Margin = (EBITDA/Sales) x 100 (8)
7	Pre-Tax Profit Margin (PTM)	PTM = (Earnings Before Tax /Sales) x 100 (9)
8	Net Profit Margin (NPM)	NPM = (Profit after Tax/Sales) x 100 (10)
9	Asset Turnover (AT) Ratio	AT = Sales/ Net Assets (11)
10	Return on Equity (ROE)	ROE = Profit after Tax/Equity (12)
11	Return on Tangible Equity (ROTE)	ROTE = Net income / (Average shareholder's equity – Intangible Assets) (13)
12	Return on Assets (ROA)	ROA = Net income/Total Assets (14)
13	Return on Investment (ROI)	ROI = (Net profit/Investment) x 100 (15)
14	OCF	Operating Cash Flow Per Share Cash Flow Per Share = (Operating Cash Flow – Preference Dividends)/Common Shares Outstanding (16)

5.2 Segment B: Classification

In preparation for the classification stage, the pre-processed dataset is divided into two parts. Using 25% of the dataset, a hybrid technique is used for testing and validation that applies ensemble supervised learning algorithms for the classification of various assault types. The remaining 75% of the dataset is used to train the model.

5.2.1 Hybrid Classifier Environment

The proposed hybrid classifier (Figure 4), a hybrid ensemble ML model, combines six different types of ML models to address credit rating grade classification. Ensemble learning is a method that uses the combined strength of ML models to tackle learning tasks, with each learner applying their output to the problem.

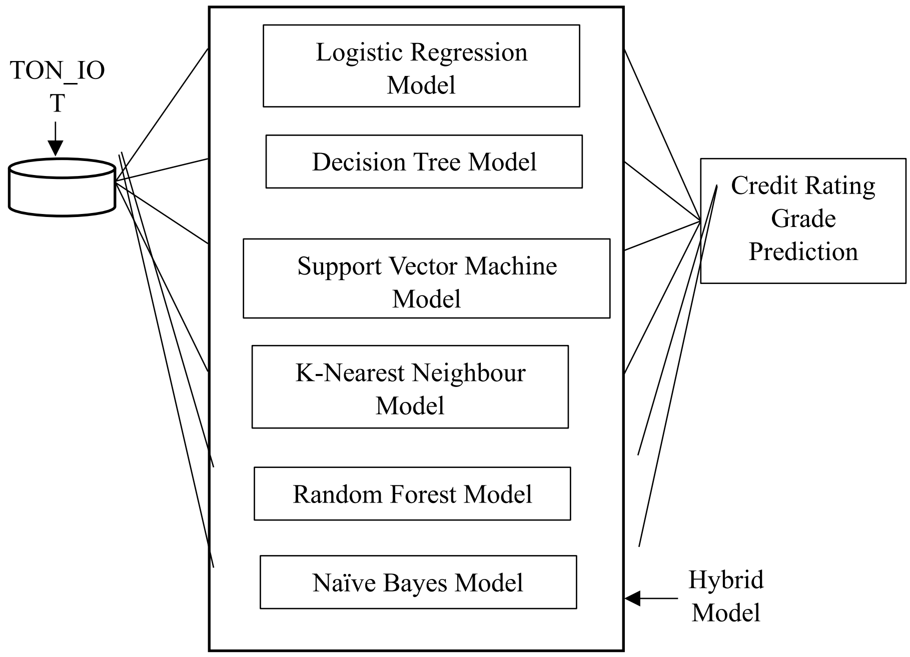


Fig. 4 Hybrid Classifier Model

In this work, a hybrid ensemble learning model that utilizes the boosting method has been built using six different types of ML models (Yadav & Singh, 2021). These models include RF, Naïve Bayes (NB), k-NN, Decision Tree (DT), SVM, and LR. This job uses a hybrid group of six ML algorithms, testing all seven datasets, contrasting with other ensemble models that use a homogenous collection.

The LR statistical model is utilized in binary classification tasks with categorical outcome variables to estimate the likelihood of a binary response based on one or more independent variables (El-Hallak, 2022). The logistic function model links independent factors to binary outcome probability, offering efficiency, interpretability, and simplicity compared to linear regression, making it widely used in big datasets (Zou et al., 2019). The DT algorithm is a popular machine learning method for classification and regression, dividing input space into homogeneous sections based on the target variable (Rokach & Maimon, 2005). Decision trees help comprehend the underlying decision-making process since they are simple to interpret and visualize (Navada et al., 2011). Techniques like trimming and ensemble methods can reduce overfitting, while SVM, a powerful supervised machine learning algorithm, can solve regression and classification issues (Han & Yao, 2023). It works by identifying the input space hyperplane that most effectively separates the different classes (Veisi, 2023). SVM is a robust, high-dimensional data processing method used in fields like bioinformatics, text classification, and picture recognition due to its ability to handle high-dimensional data.
K-NN is a simple machine learning technique suitable for regression and classification problems, allowing predictions by finding the closest K training set data points. It's non-parametric and uses K as a key hyperparameter (Tang et al., 2018) . While KNN is easy to understand and apply, computing it for big datasets can be expensive (Syriopoulos et al., 2023). In RF, an ensemble learning approach, many decision trees are joined to improve performance in classification or regression. It works by creating a forest of trees, and training each tree with a distinct subset of attributes and training data (Cao, 2022). RF is a noise-resistant decision tree that effectively handles large, high-dimensional datasets, reducing overfitting and capturing complex relationships in the data (Breiman, 2001). NB is a stochastic machine learning algorithm, based on the Bayes theorem, used for classification tasks like recommendation systems, spam filtering, and text classification (Krichene, 2017). It uses less training data and is computationally effective in estimating the necessary parameters (Acito, 2023). The Max Voting Classifier method is used to determine the final class prediction of the ensemble model by combining the five definitions of six ML models whose steps are as follows.

1. *Ensemble of Classifiers:* Training of multiple classifiers is accomplished on the given dataset, and each classifier making predictions on a given input is noted down.
2. *Voting:* In a max voting classifier, each classifier "votes" for a particular class. The class that receives the most votes is then considered the final prediction.
3. *Decision Rule:* The decision rule is typically simple: choose the class with the maximum number of votes. If there is a tie, additional rules (like random selection or using the class with the highest confidence) may be applied.
4. *Cross-Validation:* This assignment takes advantage of cross-validation, an ML approach that assesses a model's performance on unseen data (Santos et al., 2018). The procedure is iterated multiple times, with each validation set serving a distinct fold. The final result is the total, providing a more reliable assessment of the model's performance with a 10-fold cross-validation at the end.

The concept and steps of cross-validation are shown in Figures 5 and 6 respectively. Figure 7 shows the pseudo-code of the steps of the hybrid ensemble classifier model.

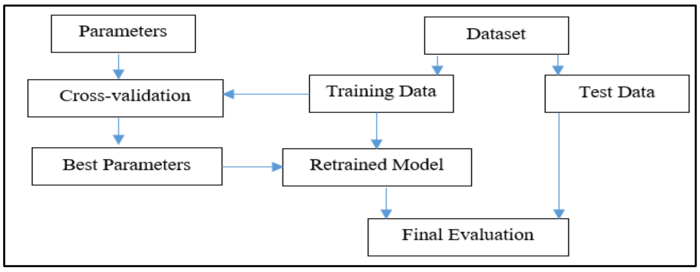


Fig. 5 Cross-validation Concept

```
Input: data X, y, and model M
Output: average accuracy of M on X, y
Step1: Shuffle the data randomly
Step 2: Split the data into 10 equal folds
Step 3: Initialize an empty list to store the accuracies
Step 4: Repeat for each fold
          for I in range (10):
          Step 4.1: Use the ith fold as the test set and the rest as the training set
          Step 4.2: Train the model on the training set
          Step 4.3: Evaluate the model on the test set and append the accuracy to the list
Step 5: Calculate and return the average accuracy
```

Fig. 6 10-fold Cross-Validation Steps

```
Step 1: Split the dataset into training and testing parts
Step 2: Define the machine learning models
          Model1 = LogisticRegression()
          Model2 = DecisionTree()
          Model3 = SVC()
          Model4 = knn()
          Model5 = RandomForest()
          Model6 = GaussianNB()
Step3: Train the machine learning models
Step 4: Make the prediction
Step 5: 10-fold Cross-Validation
Step 6: Define Hybrid Ensemble Learning Model
          Create sub-models
          estimators = []
          Step 6.1: Define 5 LR classifiers
          Step 6.2: Define 5 DT classifiers
          Step 6.3: Define 5 SVC classifiers
          Step 6.4: Define 5 knn classifiers
          Step 6.5; Define 5 RF classifiers
          Step 6.6: Define 5 GNB classifiers
Step 7: Define Ensemble model
          ensemble = VotingClassifier(estimators, voting = 'hard')
          ensemble.fit(X_train, y_train)
          y_pred = ensemble.predict(X_test)
Step 8: 10-fold Cross-Validation
          Results = model_selection.cross_val_score(ensemble, X_train, y_train, cv=kfold)
          Print (results.mean())
          print ('Accuracy of Hybrid Model =', results.mean())
```

Fig. 7 Hybrid Classifier Steps

5.2.2 Simulation Result

Corporate Credit Rating Grade Classification - The classification was performed using a hybrid ensemble ML classifier, which includes six algorithms including LR, DT, SVM, k-NN, RF, and NB. Table 2 shows the performance metrics including accuracy, precision, recall, specificity, F1_score, and AUC for corporate credit rating grade classification (0/1) using individual classifiers. Performance metrics whose expressions are shown in Eq (17) – Eq (21) indicate the acceptable performance of the model (Paul Fergus, n.d.).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (17)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (18)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (19)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+TP}} \quad (20)$$

$$\text{F1 score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \quad (21)$$

Table 2 Performance Metrics of Classification of Corporate Credit Rating Grade for Individual Classifiers

Dataset	Classifier Model	Accuracy	Precision	Recall	Specificity	F1_score	AUC
SHOPS	LR	0.7883	0.7804	0.7802	0.7802	0.7799	0.78
	DT	0.8734	0.8910	0.8910	0.8910	0.8910	0.90
	SVM	0.7880	0.8291	0.8241	0.8241	0.8230	0.78
	KNN	0.8460	0.8067	0.8021	0.8021	0.8008	0.80
	RF	0.9091	0.7804	0.7802	0.7802	0.7799	0.90
	NB	0.5989	0.7804	0.7802	0.7802	0.7799	0.68
TELCM	LR	0.7588	0.7422	0.7413	0.7413	0.7416	0.74
	DT	0.8923	0.9486	0.9482	0.9482	0.9481	0.96
	SVM	0.7804	0.7804	0.7758	0.7758	0.7760	0.74
	KNN	0.8972	0.8703	0.8620	0.8620	0.8620	0.87
	RF	0.9096	0.7422	0.7413	0.7413	0.7416	0.94
	NB	0.7028	0.7422	0.7413	0.7413	0.7416	0.71
BUSEQ	LR	0.7418	0.7242	0.7286	0.7286	0.7207	0.69
	DT	0.8757	0.8446	0.8449	0.8449	0.8428	0.83
	SVM	0.7981	0.7966	0.7984	0.7984	0.7957	0.69
	KNN	0.8330	0.8124	0.8139	0.8139	0.8123	0.80
	RF	0.9049	0.7242	0.7286	0.7286	0.7207	0.90
	NB	0.7575	0.7242	0.7286	0.7286	0.7207	0.68
DURBL	LR	0.8836	0.8343	0.8076	0.8076	0.8102	0.82
	DT	0.9109	1.0	1.0	1.0	1.0	0.95
	SVM	0.8836	0.9638	0.9615	0.9615	0.9611	0.82
	KNN	0.8654	0.9316	0.9230	0.9230	0.9210	0.90
	RF	0.9209	0.8343	0.8076	0.8076	0.8102	0.95
	NB	0.8081	0.8343	0.8076	0.8076	0.8102	0.76
HLTH	LR	0.8016	0.8123	0.8103	0.8103	0.8091	0.81
	DT	0.9096	0.9486	0.9482	0.9482	0.9481	0.93
	SVM	0.8403	0.8448	0.8448	0.8448	0.8445	0.81
	KNN	0.9099	0.9188	0.9137	0.9137	0.9138	0.92
	RF	0.9007	0.8123	0.8103	0.8103	0.8091	0.93
	NB	0.6559	0.8123	0.8103	0.8103	0.8091	0.71
ENRGY	LR	0.7831	0.7674	0.7674	0.7674	0.7674	0.77
	DT	0.9297	0.9571	0.9534	0.9534	0.9531	0.96
	SVM	0.8213	0.8861	0.8837	0.8837	0.8829	0.77
	KNN	0.8887	0.9201	0.9186	0.9186	0.9182	0.91
	RF	0.9181	0.7674	0.7674	0.7674	0.7674	0.95

	NB	0.6359	0.7674	0.7674	0.7674	0.7674	0.69
OTHER	LR	0.7974	0.7884	0.7882	0.7882	0.7878	0.79
	DT	0.8891	0.8751	0.8705	0.8705	0.8697	0.87
	SVM	0.7958	0.8300	0.8294	0.8294	0.8290	0.79
	KNN	0.8521	0.9060	0.9058	0.9058	0.9058	0.91
	RF	0.9127	0.7884	0.7882	0.7882	0.7878	0.89
	NB	0.6893	0.7884	0.7882	0.7882	0.7878	0.76

We have made a comparative analysis of the above-mentioned classifiers along with the Hybrid classifier to get an estimate of the accuracy and confusion matrix of our hybrid model on the test dataset. Table 3 shows the performance metrics of the Hybrid classifier for Corporate Credit Rating Grade classification. It mentions the accuracy, precision, recall, specificity, F1_score, R2 score, MSE, confusion matrix, and AUC (Naidu et al., 2023). The concept of the confusion matrix is depicted in Figure 8. The confusion matrix shows the number of true values and predicted values. True negatives (TN) are the numbers that show true non-investment grade predicted as non-investment grade; true positives (TP) are the numbers that show true investment grade predicted as investment grade; false negatives (FN) are the numbers that show true non-investment grade predicted as investment grade; and false positives (FP) are the numbers that show true non-investment grade predicted as an investment grade. The ratio of accurately predicted instances to all instances is known as accuracy.

True Non-investment Grade (0)	TN	FP
True Investment Grade (1)	FN	TP
	Predicted Non-investment Grade (0)	Predicted Investment Grade (1)

Fig. 8 Concept of Confusion Matrix

The Receiver Operating Characteristic (ROC) curve is a statistical tool used to evaluate the effectiveness of a classification model. The AUC represents the likelihood of assigning a higher score to a positive case than a negative one (Ampountolas et al., 2021). The Receiver Operating Characteristic (ROC) curve is a statistical tool used to evaluate the effectiveness of a classification model. The AUC represents the likelihood of assigning a higher score to a positive case than a negative one. The R2 score, a coefficient of determination, indicates how well a model matches data. The Mean Squared Error (MSE) measures the difference between actual and projected values. The Hybrid classifier's performance metrics for corporate credit rating are shown in Table 3 and Figure 9.

Table 3 Performance Metrics of Hybrid Classifier for Corporate Credit Rating

Dataset	Accuracy	Precision	Recall	Specificity	F1_score	R2 Score	MSE	Cross-Validation output	Confusion Matrix	AUC
SHOPS	0.8487	0.8651	0.8571	0.8571	0.8559	0.6833	0.14	1.0	$\begin{pmatrix} 31 & 9 \\ 6 & 41 \end{pmatrix}$	0.91
TELCM	0.8492	0.8448	0.8448	0.8448	0.8445	0.7775	0.14	0.8108	$\begin{pmatrix} 26 & 5 \\ 6 & 21 \end{pmatrix}$	0.98
BUSEQ	0.8330	0.8045	0.8062	0.8062	0.8040	0.6709	0.19	0.8330	$\begin{pmatrix} 35 & 15 \\ 10 & 69 \end{pmatrix}$	0.90
DURBL	0.9318	0.9638	0.9615	0.9615	0.9611	0.8364	0.03	0.9218	$\begin{pmatrix} 16 & 0 \\ 1 & 9 \end{pmatrix}$	0.95
HLTH	0.8843	0.9106	0.8947	0.8947	0.8912	0.8590	0.10	0.8791	$\begin{pmatrix} 28 & 3 \\ 4 & 23 \end{pmatrix}$	0.98
ENRGY	0.8711	0.8900	0.8837	0.8837	0.8823	0.9195	0.116	0.8682	$\begin{pmatrix} 31 & 8 \\ 2 & 45 \end{pmatrix}$	0.96
OTHER	0.8284	0.8411	0.8411	0.8411	0.8411	0.7708	0.15	0.8284	$\begin{pmatrix} 76 & 13 \\ 14 & 67 \end{pmatrix}$	0.92

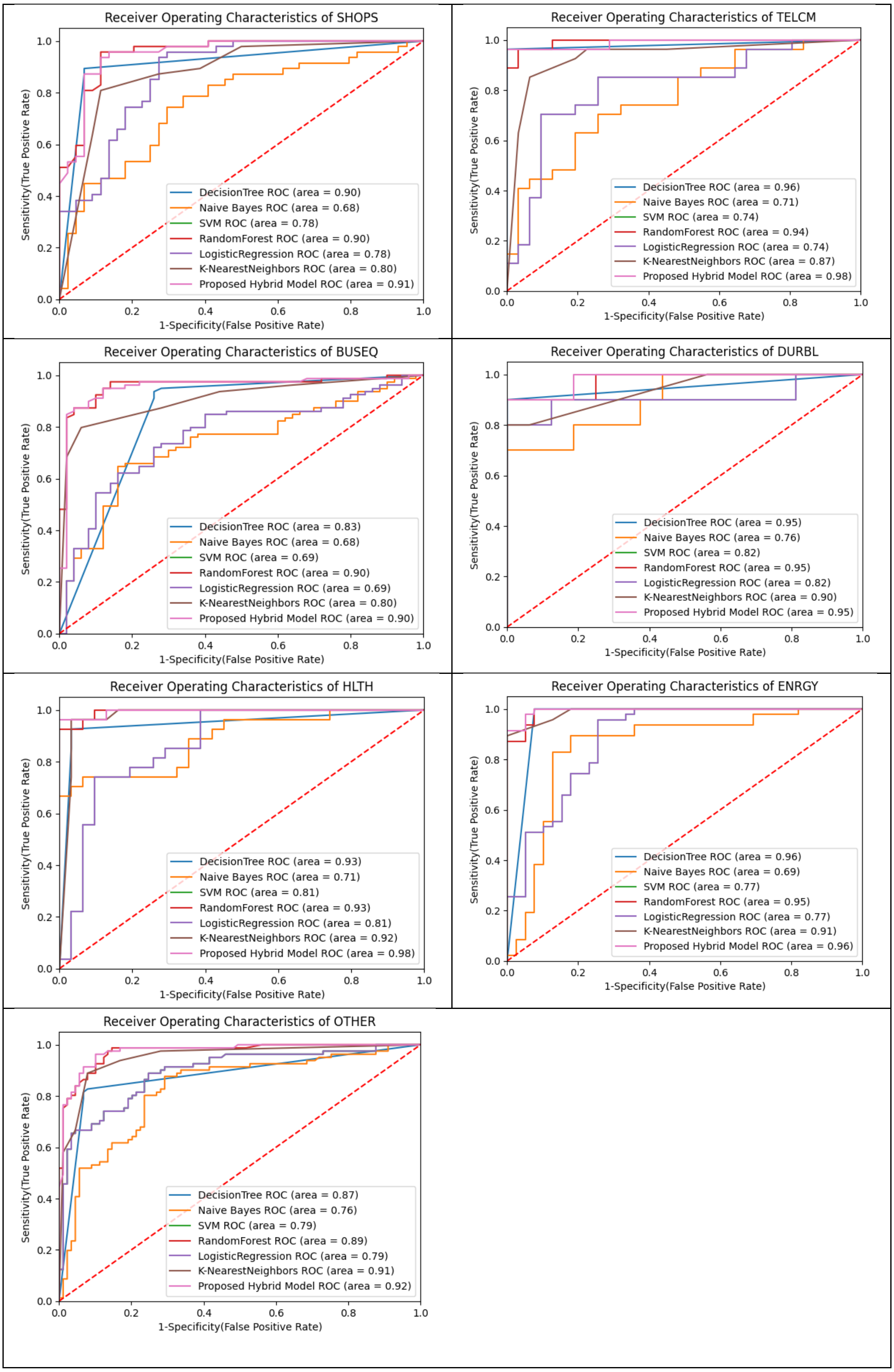


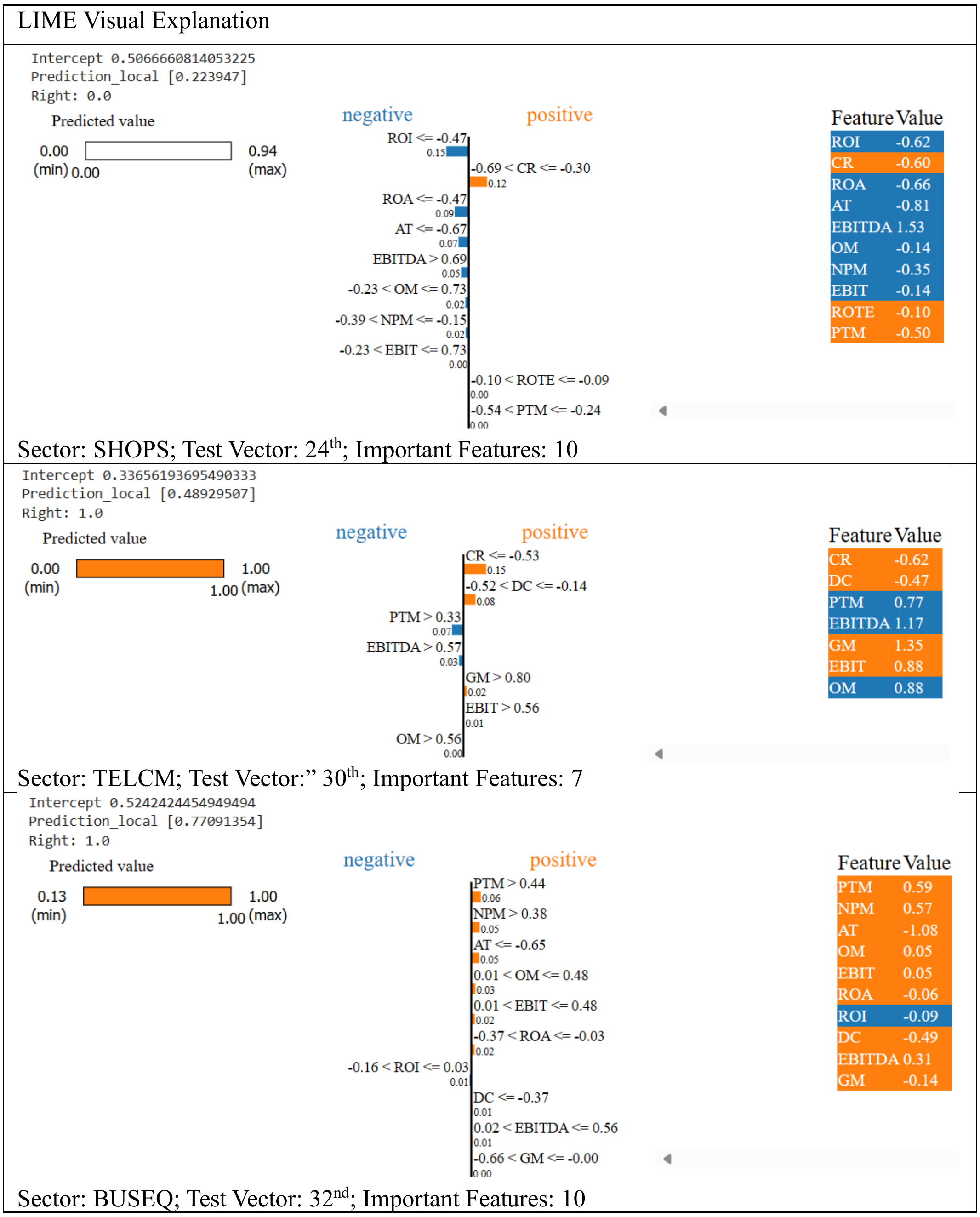
Fig. 9 ROC-AUC Curves of all the sectors for different classifiers

5.3 Segment C: Explanation

This section provides interpretations and justifications for the classification outcome.

5.3.1 LIME Explanation

At this level, the model-agnostic and local explanations of the result obtained in step 2 have been performed using LIME for the Hybrid classifier (Ng et al., 2022). "Model agnosticism" describes LIME's ability to explain any given supervised learning model in terms of a "black box" that is apart from the model after the model has been trained on the dataset. When we talk about local explanations, we mean the LIME explanations that make sense locally given the observation or sample under consideration. After obtaining a prediction model and a test sample, LIME creates 5000 feature vector samples and obtains a surrogate dataset. Next it selects features from this dataset followed by training an Extra Trees Regression on the samples in addition to preprocessing the data by using these features. Finally, it produces the local explanation for a given test sample. Figure 10 depicts the LIME visual explanations for all seven datasets.



Sector: SHOPS; Test Vector: 24th; Important Features: 10

Sector: TELCM; Test Vector:" 30th; Important Features: 7

Sector: BUSEQ; Test Vector: 32nd; Important Features: 10

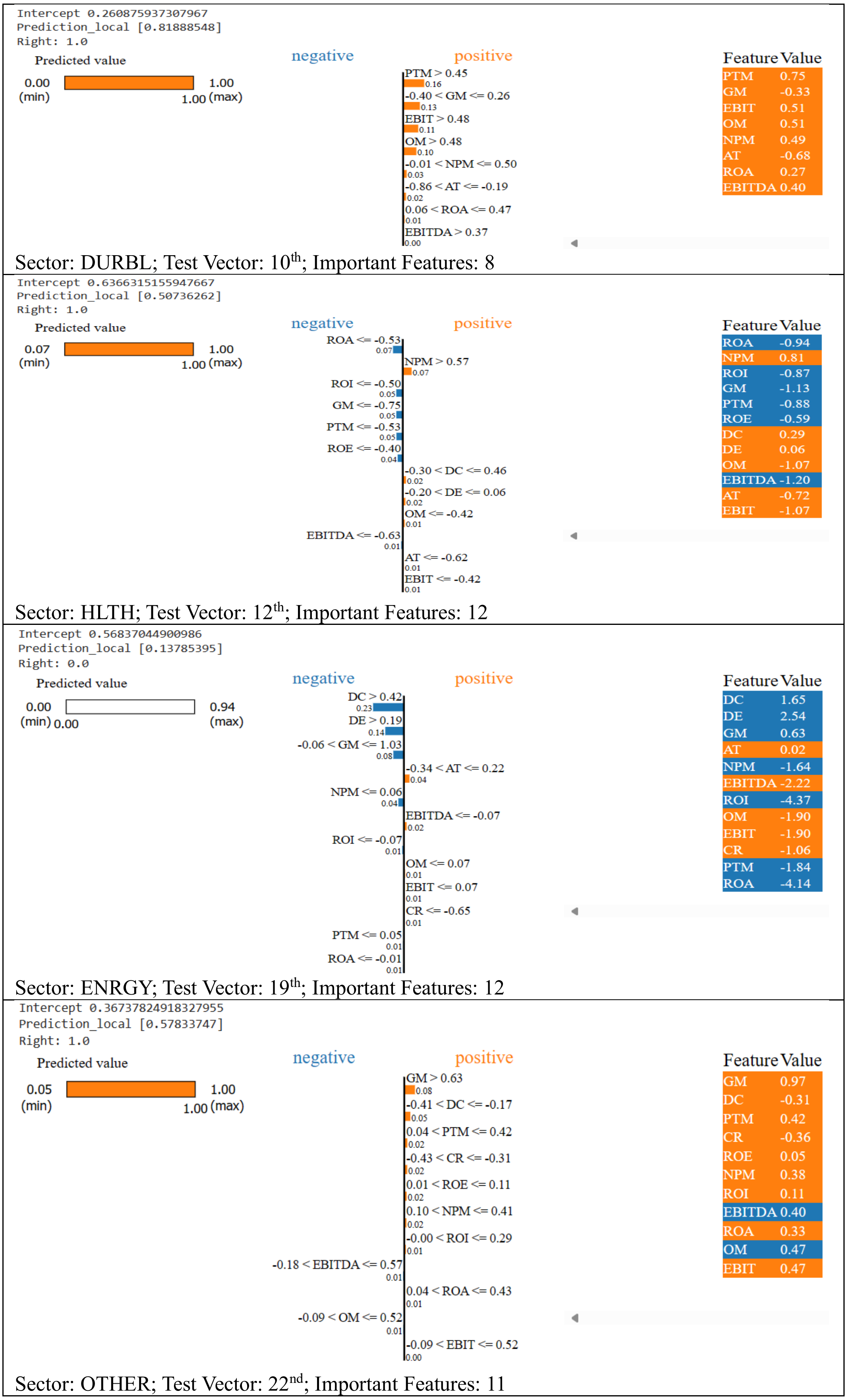
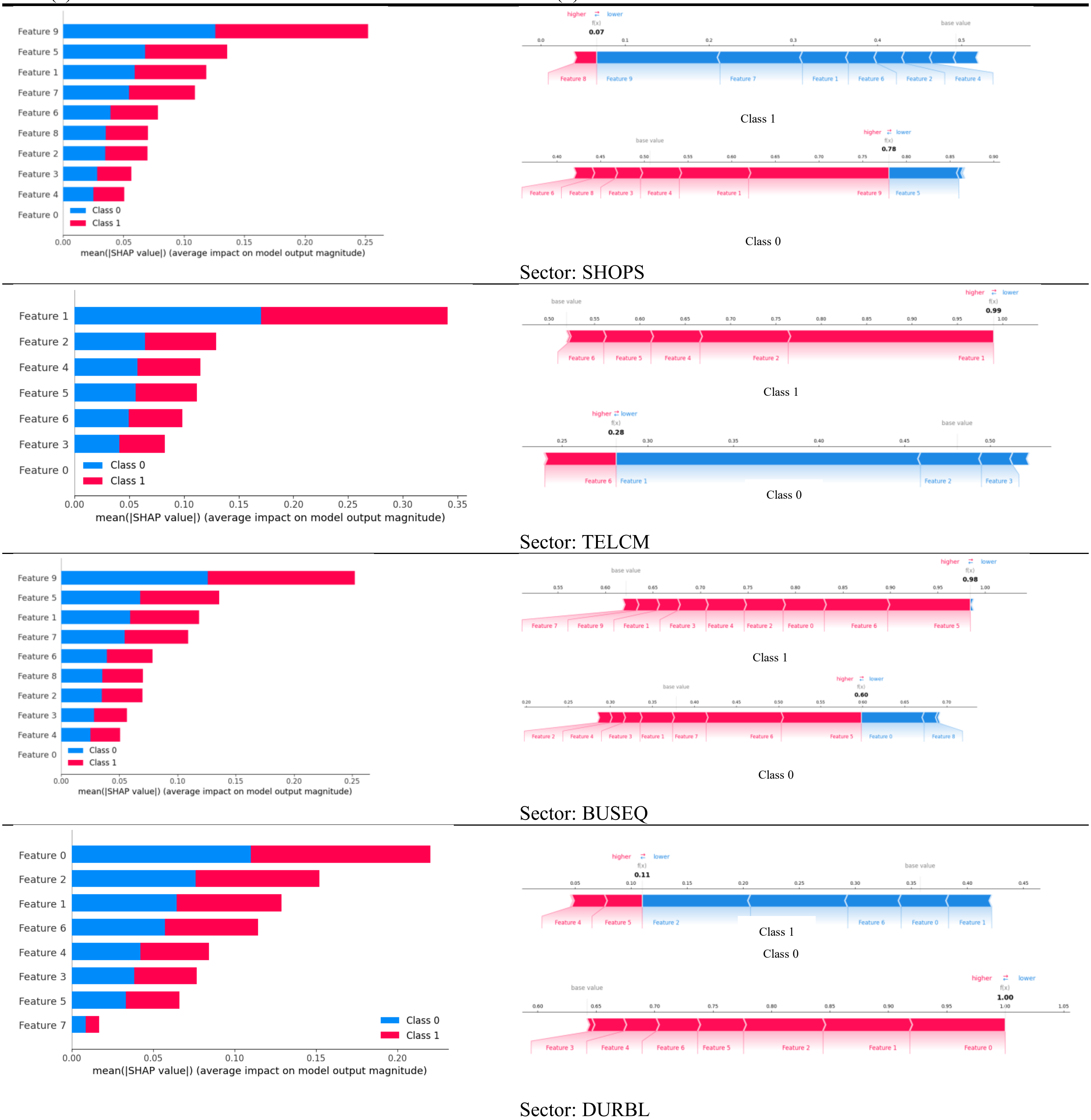


Fig. 10 LIME Explanations

5.3.2 SHAP Explanations

SHAP explanations have been applied in this stage. Using the Shapley value from game theory, the XAI method known as SHAP offers comprehensible and elucidating insights into the variables that are most significant and pertinent to the predictions made by the Hybrid classifier model (Shirota et al., 2021). Figure 11a displays the mean SHAP values, which indicate the average impact on model output magnitude and Figure 11b depicts the important features of the Hybrid Model's prediction for the two classes using force plots.

(a) SHAP Values (b) Force Plots



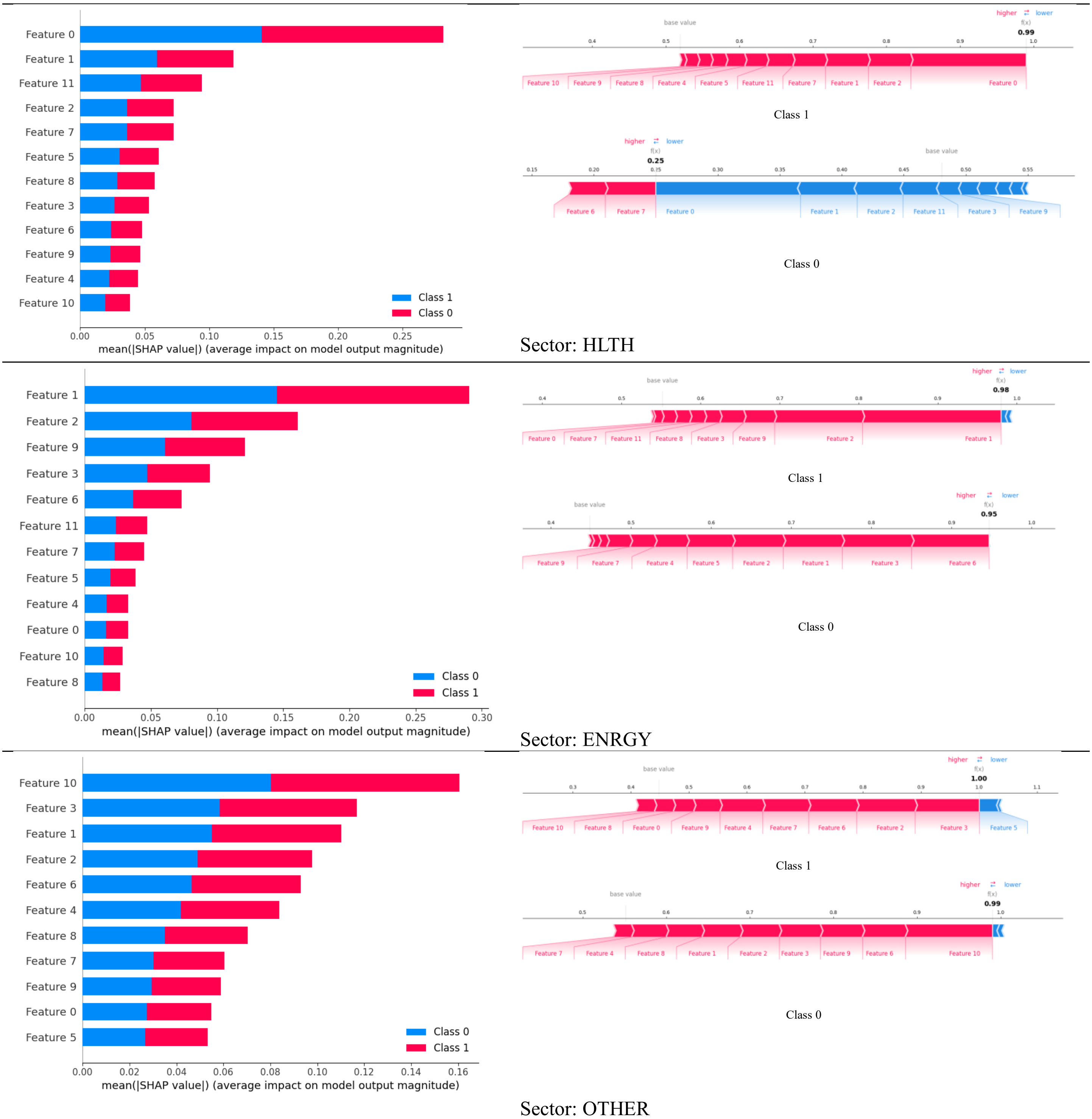


Fig. 11 Mean SHAP Values (Average Impact on Hybrid Model's Output) and Force Plots

5.4 Performance Analysis and Discussion

Table 2 and Table 3 depict the corporate credit rating grade classification performance of individual classifiers and the hybrid classifier respectively. RF classifier seems to give the best accuracy score (>90%) for all the sectors. However, for DURBL and ENRGY sectors DT equally shows good result (>90%), and for HLTH sector, both DT and k-NN compete with RF. DT classifier shows the best precision, recall, specificity, and F1_score for all the sectors except OTHER sector where k-NN outperforms all others. AUC values show the optimum performance of RF classifier; DT shows the good result for SHOPS, TELCM, DURBL, HLTH, and ENRGY whereas k-NN shows the satisfactory result for the HLTH sector.

The performance of the Hybrid classifier shows an accuracy score of >93% for the DURBL sector, which is the highest among all the accuracy scores of all the individual classifiers and all sectors. It shows the highest precision, recall, specificity and F1 scores for the DURBL sector (>96%), The confusion matrices of the seven sectors show quite low values of TN and TP indicating a pretty accurate prediction. In any scenario where the values of FP and FN are zero, the prediction is perfect. The Confusion Matrix (Table 3) of the SHOPS sectors for the Hybrid classifier shows that few false predictions exist → true class 0 predicted as class 1 (9 samples); true class 1 predicted as class 0 (6 samples). R2 score of 0.6683, MSE of 0.14, Cross-Validation of 1.0, and AUC of 0.91. The remaining sectors can be analysed similarly.

The ROC-AUC curves of the SHOPS sector for individual and Hybrid classifiers respectively show that latter outperforms all others with an AUC of 0.91. RF and DT follow next in line with AUC of 0.90 each. The other sectors may be analyzed from the plots similarly. In summary, DT, RF and Hybrid classifiers are best suited to classify the corporate credit rating grade in the present body of research.

The output of LIME may be interpreted from Figure 10 that provides a summary of the prediction model, which are the results of training a linear model on perturbed samples by an extra-trees regressor. Regarding the visualizations, it can be observed that the hues orange and blue, respectively, represent positive and negative connections between the target and the feature. An interpretation of the dataset's predictions for the SHOPS sector can be analysed as follows: The predicted value of 0.0 (0.00_{min} to 0.94_{max}) of the 24^{th} test vector showing 10 important features can be attributed to the predicted value. 'OM', 'NPM', 'EBIT', 'ROI', 'ROA', 'AT' have high negative associations and "EBITDA" have low negative associations, whereas 'ROTE', 'CR' and "PTM" have low positive associations. Similarly, the other plots of the remaining sectors explain the importance of the respective number of features and the test vector as depicted in the plots.

The mean SHAP values that have an average influence on the prediction output of the hybrid model are shown in Figure 11a. The summary graphic shows the feature significance of every feature in the model for every dataset. The lengths of the bars show how important each element is. The legend of the corresponding graphs uses many colours to indicate how much a feature contributes to each class's prediction. The results of ENRGY and TELCM sectors show that Feature 1 (DC) plays a major role in determining the results. SHOPS and BUSEQ sectors show the importance of Feature 9 (AT), DURBL and HLTH sectors show the importance of Feature 0 (CR), whereas Feature 10 (ROE) plays a major role in the OTHER sector. The plots also indicate 2 classes of the dataset (0→non-investment grade, 1→investment grade). Figure 11b shows SHAP force plots to depict the features that propel the model's output from the base value, or average forecast to the actual prediction. The features are shown by coloured bars, where red indicates positive contributions and blue indicates negative ones. The length of the bar is proportional to the magnitude of the contribution. The plot also shows the value of each feature for the instance or the group of instances being explained. For example, the SHOPS sector shows the importance of Feature 8 (positive contribution) and Features 9, 7, 1, 6, 2, and 4 (negative contribution) to the prediction result of class 1 (investment grade). The plot also shows the base value. Similarly, the other plots of the remaining sectors explain the importance of their respective features depicted in the plots.

6 Comparative Performance Analysis

In this section, a performance comparative analysis of accuracy and or AUC is made with eight related datasets in assessing credit ratings. Table 4 depicts that the proposed model surpassed all other datasets in terms of either accuracy, AUC, or both. Except for two datasets such as Bussmann N, Giudici P, Marinelli D, Papenbrock J (2021) and Misheva,Branka Hadji,Osterreider,joerg,Hirsa,Ali,Kulkarni Onkar LS fung (2021) , no other dataset uses XAI like the proposed model.

Table 4 Accuracy and AUC Comparison of Credit Rating Datasets and Related AI Models

Paper	Dataset	XAI Tool	AI Model	Accuracy/ AUC	Main Findings
Golbayani P, Florescu I, Chatterjee R (2020)	Bloomberg and Compustat dataset comprising 52 stocks of the financial sector, 8 stocks of the energy sector, and 44 stocks of healthcare sector	NA	Bagged DT, RF, SVM, and Multilayer Perceptron (MLP)	Maximum accuracy of 84.45% with RF in the energy sector	Decision tree-based models perform better, with SVM and ANN producing the most successful results.

Pol S, Hudnurkar M, Ambekar SS (2022)	Raw financial Data of IT sector companies spanned from 2014 to 2020, collected from prowessIQ database, financial statements of the companies, etc	NA	MLP, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM)	Accuracy of 87.80% (MLP), 62.69% (CNN), 56.70% (LSTM)	MLP outperforms BFGS solver in predicting credit ratings using unconstrained nonlinear optimization problem based on actual financial variables.
Alonso A, Carbó JM (2021)	Anonymized dataset from Banco Santander	NA	Logit, Lasso penalized LR, CART, RF, XGBoost, Deep Neural Network	Accuracy of 78% (Logit), 79% (Lasso), 81% (CART), 81% (Deep Neural Net), 83% (RF), and 84% (XGBoost)	Implementing XGBoost has yielded savings from 12.4% to 17% in terms of regulatory capital requirements under the IRB approach.
Bussmann N, Giudici P, Marinelli D, Papenbrock J (2021)	A dataset composed of official financial information (balance-sheet variables) on 15,045 SMEs, mostly based in Southern Europe	TreeSHAP	XGBoost	AUC of 0.81 (LR), 0.93 (XGBoost)	Network-based XAI models can significantly enhance our comprehension of the factors that contribute to financial risks, particularly credit risks.
Khemakhem S (2018)	Tunisian commercial bank dataset covering 400 observations	NA	LR, ANN, SVM	AUC of 0.8756 (ANN), 0.8480 (linear kernel SVM), 0.8476 (polynomial kernel SVM), 0.8097 (LR), and 0.7493 (Sigmoid kernel SVM)	Radial Basis Function kernel SVM outperforms all with regard to accuracy, sensitivity, and specificity with the least error rates.
Misheva,Branka Hadji,Osterreider, joerg,Hirsa,Ali,Kulkarni Onkar LS fung (2021)	open-access dataset offered by the US-based P2P Lending Platform, Lending Club	LIME and SHAP	LR, SVM, XGBoost, Neural Network, RF	Accuracy of 0.9978 (LR), 0.9971 (SVM), 0.9932 (XGBoost), 0.99487 (Neural Network), and 0.9998 (RF)	LIME and SHAP provide consistent explanations that align with financial logic with the 20 most stable features.
Raaij WF Van (2025)	133.152 mortgage and credit card customers of 3 European lenders	NA	Neural Network, RF	Accuracy is 99% (Dutch Bank Insurance Company), 95% (Dutch Mortgage Bank), 77% (British Credit	Highlights potential advantages of advanced ML techniques and unstructured data in providing faster, predictive, and prescriptive customer experience.

				Card Company)	
Xu Y, Zhang J, Hua Y, Wang L (2019)	Sellers credit cases from Taobao, which has 609 cases	NA	Three hybrid algorithms viz., DT—ANN, DT—LR, and DT—Dynamic Bayesian Network (DBN)	Accuracy of 88.864% (ANN), 79.803% (LR), 71.921% (DBN), and AUC of 0.939 (ANN), 0.892 (LR), 0.806 (DBN)	Combination of DT and ANN offers highest accuracy, facilitating efficient & fast transactions.
Proposed Model	Datasets of corporate credit rating from seven US-based industrial sectors	LIME and SHAP	Hybrid Ensemble using six supervised ML classifiers	Accuracy of 93% for the DURBL sector and AUC of 0.98 for the TELCM and the HLTH sectors using the hybrid model	Prediction of corporate credit rating investment and non-investment grades for seven US-based industrial sectors.

7 Conclusion

The paper has proposed a vital facade of corporate credit rating in the form of an XAI-based prediction model that analyses datasets from seven US-based industrial sectors to distinguish between investment-grade and non-investment-grade credit ratings. The shops, telecommunication, business equipment, durable, health, energy, and other industrial sectors are analysed using a hybrid ensemble machine-learning model that uses six machine-learning algorithms such as DT, NB, SVM, RF, LR, and k-NN. The simulation results show that the hybrid model works best for the DURBL sector with a 93% accuracy and 0.98 AUC for the TELCM and HLTH sectors. For the analysis, an SLR was conducted using the PRISMA model to identify 70 research papers that fulfilled the inclusion and exclusion criteria. The SLR of related papers were segregated into three main categories including credit rating affecting stock market prices, credit rating affecting stock liquidity, and AI-based credit rating models. The performance metrics of the classification result of the investment-grade and non-investment-grade credit ratings were supported by XAI tools like LIME for local explanation and SHAP for global explanation. Furthermore, the paper has made a comparative performance analysis with eight other related datasets in accessing credit ratings. The performance of the proposed model proved to excel among others concerning accuracy, AUC, and XAI usage. In the future, the present body of research may be extended to analyse other industrial sectors for credit rating prediction.

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