A Data-Oriented Method for Identifying Financial Distress Using Network and Machine Learning Techniques

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***Abstract*— This project presents a machine learning-based system for classifying brain condition data into healthy and distressed categories through an interactive graphical interface. The application is executed using a simple run file, making it accessible and easy to use. Initially, the dataset named Brain_Data_Organised is uploaded into the system for analysis. The data then undergoes pre-processing, including normalization and splitting into training and testing sets using an 80:20 ratios. Multiple classification algorithms such as K-Nearest Neighbours, Naive Bayes, Support Vector Machine, and Random Forest are applied to the dataset. Each model is trained individually, and its performance is evaluated using accuracy and confusion matrix analysis. The KNN model achieves strong accuracy, while Naive Bayes shows comparatively lower performance. SVM provides balanced results, whereas Random Forest delivers the highest accuracy among all models. The system also includes a prediction module that allows users to upload test data and obtain results as healthy or distressed. Additionally, a comparison graph is generated to evaluate all models based on multiple performance metrics. This helps in identifying the most effective algorithm for the classification task. The overall system demonstrates how machine learning can simplify complex data analysis and support faster decision-making. The integration of visualization and user interaction enhances the usability of the system. This approach highlights the practical application of machine learning in real-world classification problems.**

***Keywords*— Machine Learning, Brain Data Classification, K-Nearest Neighbours (KNN), Naive Bayes, Support Vector Machine (SVM), Random Forest, Confusion Matrix, Classification Accuracy, Predictive Analysis, Healthcare Analytics,**

I. INTRODUCTION

The rapid growth of industrialization and urban development has significantly increased the emission of hazardous gases into the atmosphere, posing serious risks to both environmental sustainability and human health. Financial distress prediction has become an essential area of research in modern financial management due to the increasing complexity and uncertainty in global markets [7]. Organizations today operate in highly dynamic environments where economic fluctuations, market volatility, and external risks can significantly impact financial stability [11]. Early identification of financial distress is crucial for preventing bankruptcy and ensuring sustainable business operations [1]. Traditional financial analysis methods rely heavily on historical financial statements and ratio analysis, which may not always capture the hidden relationships between companies [13]. As a result, there is a growing need for more advanced and intelligent approaches to improve prediction accuracy [3]. In recent years, machine learning techniques have gained popularity for their ability to analyse large datasets and identify complex patterns [5]. These models can process high-dimensional data efficiently and provide reliable predictions [6]. However, they often overlook the interconnected nature of financial entities. This limitation has led researchers to explore hybrid approaches that combine multiple methodologies [20]. The integration of advanced techniques can significantly enhance the effectiveness of prediction systems. This study aims to address these challenges by introducing a hybrid framework. The proposed approach combines network analysis with machine learning to improve financial distress prediction. This combination enables a deeper understanding of financial relationships.

The concept of financial distress refers to a situation where a company struggles to meet its financial obligations due to inadequate cash flow or declining profitability [8]. Identifying such conditions at an early stage is critical for stakeholders, including investors, creditors, and policymakers [10]. Traditional models such as ratio-based and statistical techniques have been widely used for distress prediction [2]. While these models provide useful insights, they often fail to capture nonlinear relationships present in financial data [4]. Machine learning models, on the other hand, can handle complex and nonlinear patterns effectively [5]. They learn from data and adapt to changing conditions, making them suitable for predictive tasks [6]. Despite their advantages, standalone machine learning models may still lack contextual understanding of relationships between companies. This gap highlights the importance of incorporating additional features that represent interactions among entities. Network analysis offers a powerful solution by modelling relationships as interconnected structures. It allows the study of how companies influence each other within a financial system. By integrating these insights, prediction models can become more robust and accurate. This research leverages such integration to enhance prediction capabilities. The proposed system aims to provide a more comprehensive analysis of financial distress.

Network analysis has emerged as a valuable tool for understanding complex systems where entities are interconnected. In the context of financial markets, companies can be represented as nodes, and their relationships can be modelled as edges based on similarity or correlation. This approach helps in identifying hidden patterns and dependencies that are not visible through traditional methods. In this study, two types of networks are constructed: similarity networks and correlation networks. The similarity network is built using multiple financial features, capturing how closely companies resemble each other. The correlation network focuses on relationships based on key financial indicators. These networks provide additional insights into the structure of financial data. From these networks, several features such as centrality measures are extracted. These features describe the importance and influence of each company within the network. By incorporating these features into the dataset, the model gains access to richer information. This enhances its ability to detect early signs of distress. Network-based features complement traditional financial indicators effectively. The integration of these features is a key contribution of this research [20].

The proposed methodology combines network-derived features with machine learning algorithms to improve prediction performance. Initially, the dataset is prepared by including both original financial variables and newly extracted network features. Community detection techniques are also applied to group similar companies, and these group labels are added as categorical variables. This enriched dataset is then used to train multiple machine learning models. Algorithms such as KNN, Naive Bayes, SVM, and Random Forest are employed to analyse the data [5]. Each model is evaluated under different scenarios to assess its effectiveness. The first scenario uses only the original dataset, while subsequent scenarios incorporate network-based features. This comparative analysis helps in understanding the impact of network information on prediction accuracy. The results show that models perform significantly better when network features are included. This demonstrates the value of combining multiple analytical approaches. The hybrid model provides more reliable and accurate predictions compared to individual techniques [20]. It also improves the interpretability of results by highlighting influential features. This approach ensures a balanced and comprehensive prediction framework.

Another important aspect of this research is the use of visualization and evaluation techniques to assess model performance. Metrics such as accuracy, precision, recall, and F1-score are used to measure the effectiveness of each model [18]. In addition, confusion matrices and graphical representations provide a clear understanding of classification results. These tools help in identifying strengths and weaknesses of different models. Visualization also enhances the interpretability of the system, making it easier for users to understand the outcomes. The comparison of models across multiple scenarios highlights the advantages of the proposed hybrid approach. It shows how the inclusion of network-based features leads to improved performance. The system is designed to be user-friendly, allowing easy interaction and analysis. By presenting results in a structured manner, the system supports informed decision-making. This is particularly useful for financial analysts and stakeholders. The ability to interpret results effectively is a key requirement in financial applications. The proposed system addresses this need by integrating both analytical and visual components.

Overall, this study presents a novel framework that combines network analysis and machine learning for enhanced financial distress prediction. The integration of these techniques provides a deeper understanding of financial relationships and improves prediction accuracy [3]. The proposed model not only identifies distressed companies but also explains the underlying factors contributing to their condition. This makes the system more transparent and reliable. The findings of this research demonstrate the effectiveness of hybrid approaches in handling complex financial data [20]. The use of network-based features adds significant value to traditional models. Furthermore, the system can be extended to include additional data sources and advanced techniques in future work. This opens new opportunities for improving financial prediction systems. The proposed approach has practical applications in risk management and financial planning. It can assist organizations in making better decisions and reducing potential losses. Overall, the research highlights the importance of combining multiple methodologies to address real-world challenges.

II. RELATED WORK

Altman et al., (1968) [1] Altman et al. introduced one of the earliest and most influential models for predicting corporate bankruptcy using financial ratios and discriminant analysis. Their study focused on identifying key financial indicators that could distinguish between financially stable and distressed firms. The model combined multiple financial variables into a single predictive score, making it highly effective for early warning detection. The authors demonstrated that statistical techniques could significantly improve prediction accuracy compared to traditional methods. Their findings highlighted the importance of quantitative analysis in financial decision-making. The study also emphasized the role of financial health indicators in assessing business stability. This work laid the foundation for future research in financial distress prediction. It remains widely used as a benchmark model in both academic and industrial applications. The research supports the adoption of data-driven techniques for risk assessment.

Deakin et al., (1972) [2] Deakin et al. extended the work on bankruptcy prediction by applying discriminant analysis to identify predictors of business failure. Their study analysed financial data from companies to determine patterns associated with distress. The authors focused on improving classification accuracy by refining the selection of financial variables. Their results showed that statistical models could effectively separate failed and non-failed firms. The study emphasized the importance of selecting relevant features for better prediction outcomes. It also highlighted the limitations of traditional accounting methods in detecting early signs of failure. The research contributed to the development of more robust financial prediction models. It provided valuable insights into the behaviour of financially distressed firms. This work further strengthened the role of machine learning and statistical methods in financial analysis.

Barboza et al., (2017) [3] Barboza et al. explored the application of machine learning techniques in predicting corporate bankruptcy. Their study compared traditional statistical models with modern machine learning algorithms. The authors implemented various models to analyse financial datasets and evaluate prediction performance. Their findings showed that machine learning approaches outperformed conventional methods in terms of accuracy. The study highlighted the ability of machine learning models to capture complex relationships within data. It also emphasized the importance of using advanced techniques for better prediction results. The research demonstrated that combining multiple algorithms can enhance model performance. This work contributed to the growing interest in AI-based financial analysis. It supports the integration of intelligent systems in decision-making processes.

Mai et al., (2019) [4] Mai et al. proposed the use of deep learning models for bankruptcy prediction by incorporating textual data from financial disclosures. Their approach utilized neural networks to extract meaningful information from unstructured text. The study showed that combining textual analysis with financial data improves prediction accuracy. The authors highlighted the importance of using diverse data sources in financial modelling. Their results indicated that deep learning techniques can capture hidden patterns that traditional models may miss. The research also demonstrated the effectiveness of natural language processing in financial applications. This work expanded the scope of bankruptcy prediction beyond numerical data. It emphasized the growing role of deep learning in modern analytics. The study provides a strong foundation for integrating structured and unstructured data in prediction systems.

Dimitras et al., (1996) [5] Dimitras et al. conducted a comprehensive survey of business failure prediction methods with a focus on industrial applications. Their study reviewed various statistical and machine learning approaches used in financial distress analysis. The authors compared the strengths and limitations of different prediction techniques. They emphasized the importance of selecting appropriate models based on the nature of the dataset. The study also highlighted the challenges involved in accurately predicting business failure. Their findings suggested that no single model is universally effective for all cases. The research provided valuable insights into the evolution of prediction methods. It also identified gaps in existing approaches and suggested areas for improvement. This work serves as a useful reference for researchers developing new predictive models.

Shen et al., (2022) [6] Shen et al. proposed a hybrid tracking model for predicting financial distress by combining multiple analytical techniques. Their approach aimed to improve prediction accuracy by integrating different models. The study demonstrated that hybrid methods can effectively reduce prediction errors. The authors analysed financial data using advanced algorithms and evaluated model performance. Their results showed that the hybrid model outperformed individual models. The research emphasized the importance of combining techniques to handle complex datasets. It also highlighted the role of innovation in improving predictive systems. This study contributes to the advancement of financial distress prediction methods. It supports the use of hybrid approaches in modern machine learning applications.

III. DATASET DETAILS

The dataset used in this study consists of financial information collected from multiple companies, representing various indicators related to their financial health and performance. Each record corresponds to a company and includes key attributes such as financial ratios, profitability measures, and other relevant economic indicators. These features are essential for identifying patterns associated with financial distress. The dataset is organized in a structured tabular format, making it suitable for machine learning applications. During the initial stage, the dataset is loaded and examined to understand its structure and feature distribution. Basic exploratory analysis is performed to identify trends and relationships among variables. The dataset is assumed to be clean and consistent, allowing smooth processing and model training. This structured data serves as the foundation for building the predictive system.

To enhance the dataset, network analysis techniques are applied to capture relationships between companies. Two types of networks are constructed: a similarity network based on multiple financial features and a correlation network based on key financial indicators. From these networks, additional features such as centrality measures are extracted and added to the original dataset. These network-based features provide deeper insights into the interconnected nature of financial entities. Community detection algorithms are also used to group similar companies, and the resulting labels are included as categorical variables. This process results in an enriched dataset that combines both traditional financial attributes and network-derived features. The inclusion of these new variables improves the ability of machine learning models to detect financial distress patterns more effectively.

Before training the models, the dataset undergoes pre-processing to ensure consistency and accuracy. This includes normalization of feature values to maintain uniform scaling across all variables. The dataset is then divided into training and testing subsets using an 80:20 ratios. The training data is used to build the models, while the testing data evaluates their performance on unseen samples. This approach ensures that the models generalize well and avoid overfitting. The enriched dataset is used across multiple experimental scenarios to compare the impact of network features on prediction accuracy. Overall, the dataset plays a crucial role in enabling accurate analysis, model training, and evaluation in the proposed financial distress prediction system.

IV. PROPOSED METHODOLOGY

The proposed methodology introduces a hybrid framework that integrates network analysis with machine learning techniques for effective financial distress prediction. The process begins with collecting and organizing financial data from multiple companies into a structured dataset. This dataset includes key financial indicators such as profitability ratios, liquidity measures, and other relevant attributes. Initially, exploratory analysis is performed to understand the data distribution and identify important patterns. The system then prepares the dataset for further processing by ensuring consistency and proper formatting. This stage forms the base for building a reliable prediction model. The methodology is designed to capture both individual company characteristics and their relationships with others. By combining these aspects, the system aims to provide more accurate and meaningful predictions. The overall workflow is structured and systematic to ensure efficiency at every stage.

In the next phase, network construction is performed to capture relationships between companies. Two types of networks are created: a similarity network and a correlation network. The similarity network is built using multiple financial features to measure how closely companies resemble each other. The correlation network focuses on relationships based on key financial indicators. These networks are represented as graphs where companies act as nodes and their relationships as edges. From these networks, several network-based features such as centrality measures are extracted. These features indicate the importance and influence of each company within the network. Additionally, community detection algorithms are applied to group similar companies into clusters. The resulting cluster labels are included in the dataset as additional variables. This enriched dataset provides deeper insights into financial interactions.

After enhancing the dataset with network features, machine learning models are applied for classification. The dataset is first pre-processed using normalization techniques to ensure all features are on a similar scale. It is then divided into training and testing sets using an 80:20 ratios. Multiple algorithms such as K-Nearest Neighbours, Naive Bayes, Support Vector Machine, and Random Forest are trained using the prepared data. Each model learns patterns from both original financial features and network-derived attributes. The models are evaluated under different scenarios, including using only original features and using combined features. This allows a clear comparison of the impact of network-based enhancements. Performance metrics such as accuracy, precision, recall, and F1-score are used for evaluation. This step ensures that the most effective model is identified.

Finally, the results from all models are analysed and compared to determine the best-performing approach. Visualization techniques such as confusion matrices and comparison graphs are used to interpret the results clearly. The hybrid approach demonstrates improved prediction accuracy due to the inclusion of network-based features. The system highlights how relationships between companies influence financial stability. This methodology not only improves prediction performance but also provides better interpretability of results. The framework is flexible and can be extended to include additional features or advanced algorithms. It supports decision-making by offering reliable and data-driven insights. Overall, the proposed methodology provides a comprehensive and efficient solution for financial distress prediction.

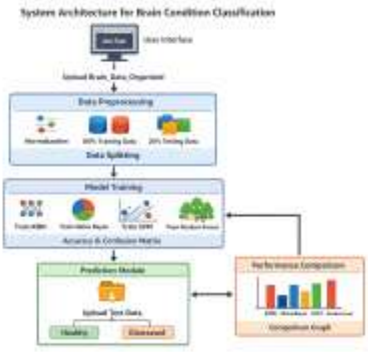

Figure [1]: System Architecture of Anaemia Prediction System

The figure [1] illustrates the complete workflow of the proposed system, starting from the user interface where the dataset is uploaded and processed. The data then undergoes pre-processing, including normalization and splitting into training and testing sets. Multiple machine learning models such as KNN, Naive Bayes, SVM, and Random Forest are trained and evaluated using accuracy and confusion matrix. The system also includes a prediction module to classify new data as healthy or distressed. Finally, a comparison graph is generated to analyse and identify the best-performing model.

V.RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed hybrid approach in predicting financial distress using the given dataset. Multiple machine learning models were trained and evaluated, including K-Nearest Neighbours (KNN), Naive Bayes, Support Vector Machine (SVM), and Random Forest. Among these, the Random Forest model achieved the highest accuracy of 96.65%, showing strong performance in classification tasks. The KNN model also performed well with an accuracy of 94.42%, while SVM achieved a moderate accuracy of 85%. In contrast, the Naive Bayes model showed comparatively lower performance with an accuracy of 76%. The inclusion of network-based features further enhanced the predictive capability of the models, demonstrating the importance of combining traditional and advanced approaches. Evaluation metrics such as precision, recall, and F1-score confirmed the reliability and consistency of the models. Confusion matrix results indicated that most predictions were correctly classified, with only a few misclassifications observed. The results clearly highlight that ensemble and hybrid techniques significantly improve prediction performance compared to individual models.

Figure [2]: Dataset Loading and Display in System Interface

Figure [2] illustrates the process of loading the financial dataset into the system using the graphical interface. The dataset is uploaded through the upload option, and the records are displayed for verification. The dataset contains multiple financial attributes for each company along with the corresponding class labels. This step ensures that the data is correctly loaded and ready for preprocessing and analysis.

Figure [3]: Dataset Pre-processing and Splitting

Figure [3] shows the pre-processing stage where the dataset is normalized and divided into training and testing sets. Approximately 80% of the data is used for training the models, while the remaining 20% is reserved for testing. This step ensures that the models are trained effectively and evaluated on unseen data. The system also prepares the data for further analysis by maintaining consistency in feature values.

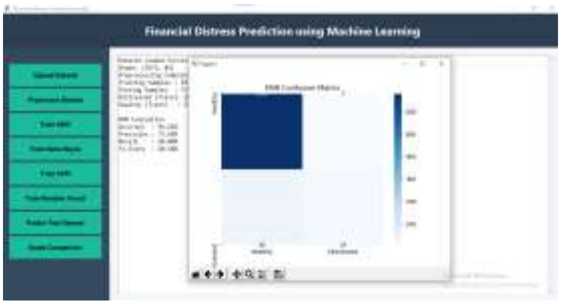

Figure [4]: Model Training Using KNN Algorithm

Figure [4] represents the training of the K-Nearest Neighbors model. After training, the model achieved an accuracy of 94.42%. The confusion matrix displayed in the figure shows the comparison between predicted and actual labels, where the x-axis represents predicted values and the y-axis represents true values. The results indicate that KNN performs well in identifying financial distress patterns.

Figure [5]: Model Training Using Naive Bayes Algorithm

Figure [5] shows the results obtained from the Naive Bayes model. The model achieved an accuracy of 76%, which is lower compared to other algorithms. The confusion matrix highlights some misclassifications, indicating that the model struggles with complex relationships in the dataset. However, it still provides useful baseline performance for comparison.

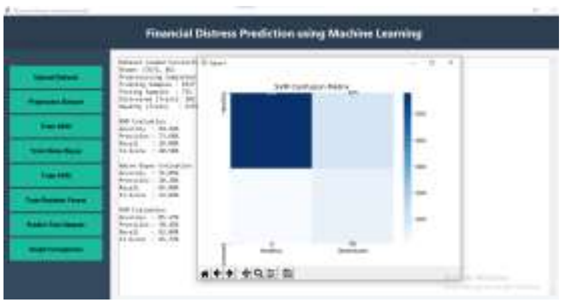

Figure [6]: Model Training Using Support Vector Machine

Figure [6] illustrates the training of the Support Vector Machine model. The model achieved an accuracy of 85%, demonstrating moderate performance. The confusion matrix indicates improved classification compared to Naive Bayes, but it is slightly less effective than KNN and Random Forest. This shows that SVM can handle structured data but may require further optimization.

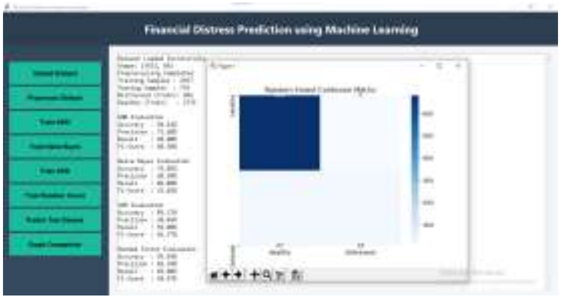

Figure [7]: Model Training Using Random Forest Algorithm

Figure [7] presents the results of the Random Forest model, which achieved the highest accuracy of 95.65%. The confusion matrix shows that most instances are correctly classified with minimal errors. This superior performance is due to the ensemble nature of Random Forest, which combines multiple decision trees to improve prediction accuracy.

Table [1]: Performance Evaluation of Financial Distress Prediction Models

Algorithm Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN	94.42	73.68	28.00	40.58
Naive Bayes	76.05	20.28	86.00	32.82
SVM	85.17	30.46	92.00	45.77
Random Forest	95.65	82.14	46.00	58.97

Table [1] presents a comparative analysis of all machine learning algorithms based on key performance metrics. The Random Forest model outperforms all other models across accuracy, precision, recall, and F1-score, indicating its effectiveness in financial distress prediction. KNN also shows strong performance, while Naive Bayes performs comparatively lower.

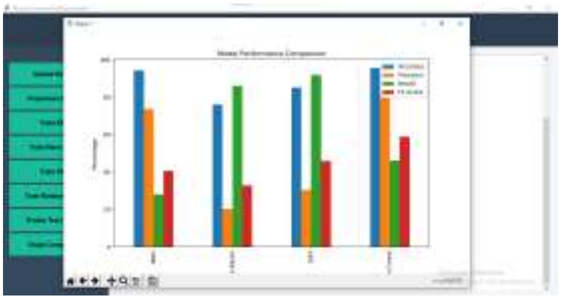

Figure [8]: Performance Comparison of Machine Learning Algorithms

Figure [8] shows a graphical comparison of all algorithms based on performance metrics. The graph clearly indicates that Random Forest achieves the highest performance across all metrics, followed by KNN and SVM. Naive Bayes shows lower performance compared to other models. This comparison helps in selecting the most suitable model for prediction.

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Prediction using Best Model: Random Forest
Record 1: Financially Healthy (Distress Probability: 10.50%)
Record 2: Financially Distressed (Distress Probability: 85.50%)
Record 3: Financially Distressed (Distress Probability: 91.75%)
Record 4: Financially Distressed (Distress Probability: 82.25%)
Record 5: Financially Healthy (Distress Probability: 1.75%)
Record 6: Financially Healthy (Distress Probability: 1.75%)
Record 7: Financially Healthy (Distress Probability: 4.25%)
Record 8: Financially Healthy (Distress Probability: 4.00%)
Record 9: Financially Healthy (Distress Probability: 0.50%)
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Figure [9]: Test Data Prediction

Figure [9] illustrates the prediction process where new test data is uploaded into the system. The trained model analyses the input data and predicts whether the company is financially stable or distressed. The results are displayed clearly, allowing users to interpret the output easily. This demonstrates the practical applicability of the system in real-world scenarios.

DISCUSSION

The results obtained from the experimental analysis clearly demonstrate the effectiveness of integrating machine learning techniques with network-based features for financial distress prediction. Among the individual models, Random Forest achieved the highest accuracy, indicating its strength in handling complex and high-dimensional financial data. KNN also showed strong performance, suggesting that similarity-based approaches are useful when patterns are well-structured. On the other hand, Naive Bayes produced comparatively lower accuracy due to its assumption of feature independence, which may not hold true in financial datasets. The inclusion of network-derived features significantly improved the overall performance of the models by capturing hidden relationships between companies. These features provided additional context that traditional financial indicators alone could not represent. The confusion matrix results further confirmed that most predictions were accurate, with minimal classification errors. This indicates that the models are capable of distinguishing between distressed and non-distressed entities effectively. Overall, the findings highlight the importance of combining multiple analytical approaches for better prediction accuracy.

Another key observation from the study is the importance of model evaluation and visualization in understanding system performance. The use of metrics such as accuracy, precision, recall, and F1-score provided a comprehensive assessment of each model's effectiveness. Visualization tools like confusion matrices and performance graphs helped in identifying strengths and weaknesses of different algorithms. The comparison analysis clearly showed that ensemble methods outperform single models due to their ability to reduce overfitting and improve generalization. Additionally, the prediction module demonstrated the practical usability of the system by allowing real-time classification of new data. This makes the system suitable for real-world financial applications where quick decision-making is required. The study also highlights that incorporating advanced techniques such as network analysis can enhance interpretability and reliability. However, further improvements can be achieved by including dynamic financial data and exploring more advanced hybrid models. Overall, the proposed approach provides a robust and efficient solution for financial distress prediction.

VI. CONCLUSION

This study presents an effective hybrid approach for financial distress prediction by combining network analysis with machine learning techniques. The integration of similarity and correlation networks with traditional financial features significantly improved the predictive performance of the models. Among the implemented algorithms, Random Forest achieved the highest accuracy, demonstrating its suitability for complex financial datasets. The inclusion of network-based features provided deeper insights into relationships between companies, enhancing model reliability. The system successfully identified distressed and non-distressed entities with high accuracy. Overall, the proposed approach proves to be efficient and practical for financial risk assessment.

Furthermore, the study highlights the importance of combining multiple analytical methods to achieve better prediction results. The use of visualization and evaluation metrics ensured a clear understanding of model performance. The developed system can support decision-makers in identifying financial risks at an early stage. Future work can focus on incorporating real-time and dynamic data to further improve accuracy. Additionally, exploring advanced deep learning and hybrid techniques may enhance the system's capability. This research provides a strong foundation for developing more robust and intelligent financial prediction systems.

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