IRJAEH

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 12 December 2025
Page No: 4187-4195
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0613

FINNET: A Hybrid Deep Learning Network Analysis and Ensemble Learning Model for Financial Distress Prediction

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Abstract
Financial distress prediction plays a crucial role in financial risk management and early warning systems. Traditional models often fail to capture the nonlinear dependencies and intercompany relationships that influence financial health. This study presents FIN-NET, a hybrid system integrating Artificial Neural Networks (ANN), ensemble learning (Voting and Stacking Classifiers), and network analysis for more accurate financial distress prediction. The system leverages K-best feature selection and K-means clustering to extract relevant financial indicators. FIN-NET classifies companies as either 'Financially Healthy' or 'Distressed' and provides explainable insights for decision-makers. The implementation uses Python (Flask, Scikit-learn, NumPy) and MySQL, which ensure modularity, scalability, and real-time prediction. Testing confirmed the system's robustness, achieving high accuracy across multiple scenarios, making it suitable for academic and financial applications.

Keywords: *Deep Learning; Ensemble Learning; Financial Distress Prediction; Machine Learning; Network Analysis, FIN-NET.*

1. Introduction
Financial distress prediction has become paramount for maintaining economic stability and protecting stakeholder interests in the current dynamic and interconnected financial environment. Traditional FDP models, such as Altman's Z-Score or standard machine learning classifiers, often fall short because they typically assess companies in isolation, failing to capture complex non-linear financial patterns and the crucial systemic risks or "ripple effects" that occur when distress propagates across interconnected business networks. To overcome these limitations, we introduce FIN-NET (Financial Network Analysis), a novel hybrid predictive system that integrates the deep pattern recognition capabilities of Artificial Neural Networks (ANN) and the robustness of Ensemble Learning techniques with Network Analysis to model inter-company dependencies. FIN-NET is engineered to provide not only superior predictive accuracy but also greater interpretability and timely detection of systemic vulnerabilities, offering a data-driven and proactive solution for investors, regulators, and financial analysts.

1.1 Related work
The evolution of Financial Distress Prediction (FDP) has been marked by a critical transition from traditional statistical methods to sophisticated artificial intelligence approaches. Historically, FDP research has been grounded in foundational techniques such as Altman's Z-Score and Logistic Regression [13], [15]. While these methods offer interpretability and simplicity, their major limitation lies in assuming linear relationships among financial indicators [3] and, crucially, treating corporate entities in total isolation, failing to account for systemic dependencies that propagate risk. To address these shortcomings, the field has rapidly adopted non-parametric Machine Learning (ML) techniques. Studies have demonstrated significant improvements in predictive power and robustness using models such as Support Vector Machines

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(SVM) [8], Random Forests (RF), and various Gradient Boosting algorithms [5], [7], particularly in handling class imbalance [4], [14]. Building upon this, Deep Learning (DL) architectures, such as Multi-Layer Perceptrons (MLP) [6], have shown a superior ability to capture intricate, hidden patterns in financial data [2]. However, the increased complexity of DL models introduces new obstacles, primarily high computational cost and significant lack of interpretability [11]. Contemporary research focuses on developing holistic hybrid systems that incorporate contextual and systemic factors. Work in this area involves ensemble learning techniques, including Voting and Stacking Classifiers [1], to blend diverse predictions for a stable and accurate outcome. Furthermore, research increasingly recognizes the non-isolated nature of corporate finance through methods such as clustering [10] and advanced feature selection mechanisms [7], [12]. Despite these continuous advancements, a key methodological gap persists: the current literature lacks a unified framework that seamlessly integrates deep nonlinear learning (MLP/ANN), the stability of sophisticated ensemble methods, and the explicit quantification of inter-firm dependencies via network centrality features. The proposed FIN-NET system was designed to fill this void.

2. Methodology

FIN-NET system employs a robust, modular, and hybrid methodology engineered to overcome the predictive and interpretative limitations of traditional models. The process follows a systematic, end-to-end pipeline, beginning with meticulous data preprocessing (including K-best feature selection and K-means clustering) to establish homogeneous risk groups. The core innovation lies in the subsequent fusion of financial metrics with novel network centrality features that quantify systemic risk propagation across inter-company linkages. This enriched dataset is fed into a multi-layered predictive engine that leverages the non-linear learning power of Artificial Neural Networks (ANN) and the enhanced stability of Ensemble Classifiers (Voting and Stacking). The overall system design, illustrated through Use Case, Data Flow, and Sequence Diagrams, ensures efficient processing, clear module interaction, and the delivery of highly accurate and transparent financial distress predictions.

2.1 System Design

The Data Flow Diagram systematically illustrates the movement of financial data The FIN-NET system is built on a layered and modular architecture that ensures robustness, scalability, and clear separation of concerns, beginning with user access control and culminating in interpretable risk prediction. The flow is initiated with the Authentication Layer, where the user validates credentials against a secure database. Upon successful login, the Core Processing Engine takes over, handling Data Preprocessing (including feature engineering and clustering) to enrich the dataset. This cleaned and augmented data then enters the Model Building phase, which is the heart of the hybrid approach: here, Artificial Neural Networks (ANN) and Ensemble Classifiers (Voting, Stacking) are trained on both standard financial ratios and contextual Network Centrality Features. The final Prediction Module classifies the firm's status as "Healthy" or "Financial Distress" and forwards the output, along with explainability insights, to the dedicated Result Output Layer, ensuring efficient, transparent, and actionable risk assessment.

2.2 Use Case

The Use Case Model outlines the key interactions between the user—acting as a financial analyst—and the FIN-NET system. The user performs basic actions such as viewing informational pages and inspecting the dataset before selecting a prediction model and entering company-specific financial inputs. Once the inputs are submitted, the system handles the full analytical workflow, including data ingestion, preprocessing, feature segmentation, and execution of the hybrid prediction engine enhanced with Network Centrality Features. The validated model then generates and displays the final classification as either “Financially Healthy” or “Distressed.” This structure ensures that the user focuses only on input and interpretation, while the system manages all computational and sequential processes autonomously.

2.3 Sequence diagram

The Sequence Diagram meticulously illustrates the real-time, chronological interactions between the User and the system's core components: The User Interface, Model Module, Prediction Module, and

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Database. The process begins with the user accessing informational or data pages, prompting the User Interface to request and display data retrieved from the database. To initiate the core analytical functionality, the user requests available models; the Model Module returns a list of models along with their stored accuracy scores, allowing the user to make a selection. Once the specific hybrid model is loaded, the user submits their financial input via the interface. This input is forwarded to the Prediction Module, which uses the trained model to execute the prediction logic, calculate the distress status, and send the result back to the User Interface for final display. This orchestrated sequence ensures a streamlined, transparent workflow that transforms raw financial input into actionable, model-based intelligence. Figure 1 shows System Architecture Showing Workflow from User Login to Prediction Figure 2 shows Use Case Diagram Illustrating The Interactions Between The User And The System

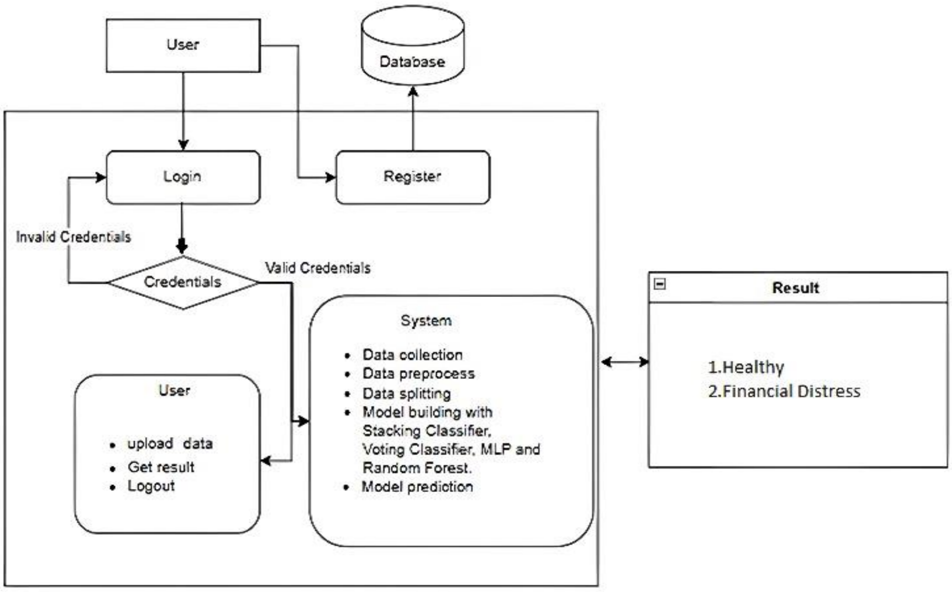

Figure 1 **System Architecture Showing Workflow from User Login to Prediction**

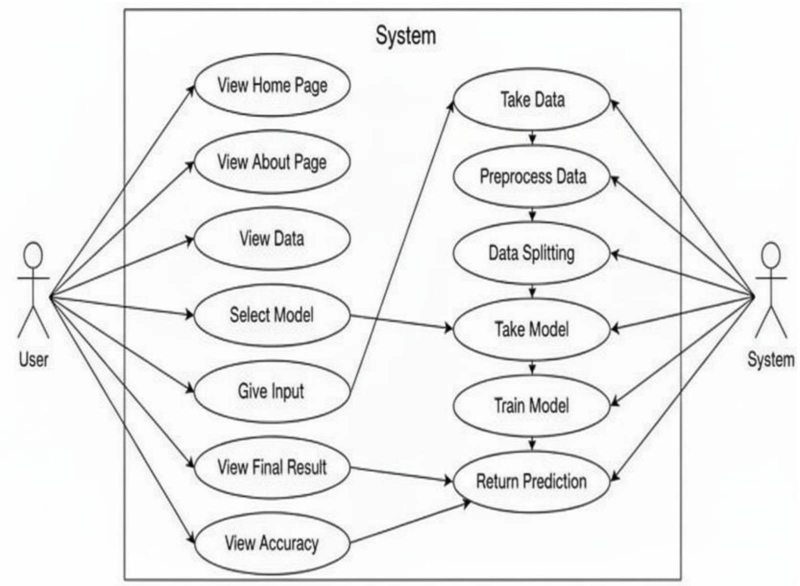

Figure 2 **Use Case Diagram Illustrating The Interactions Between The User And The System**

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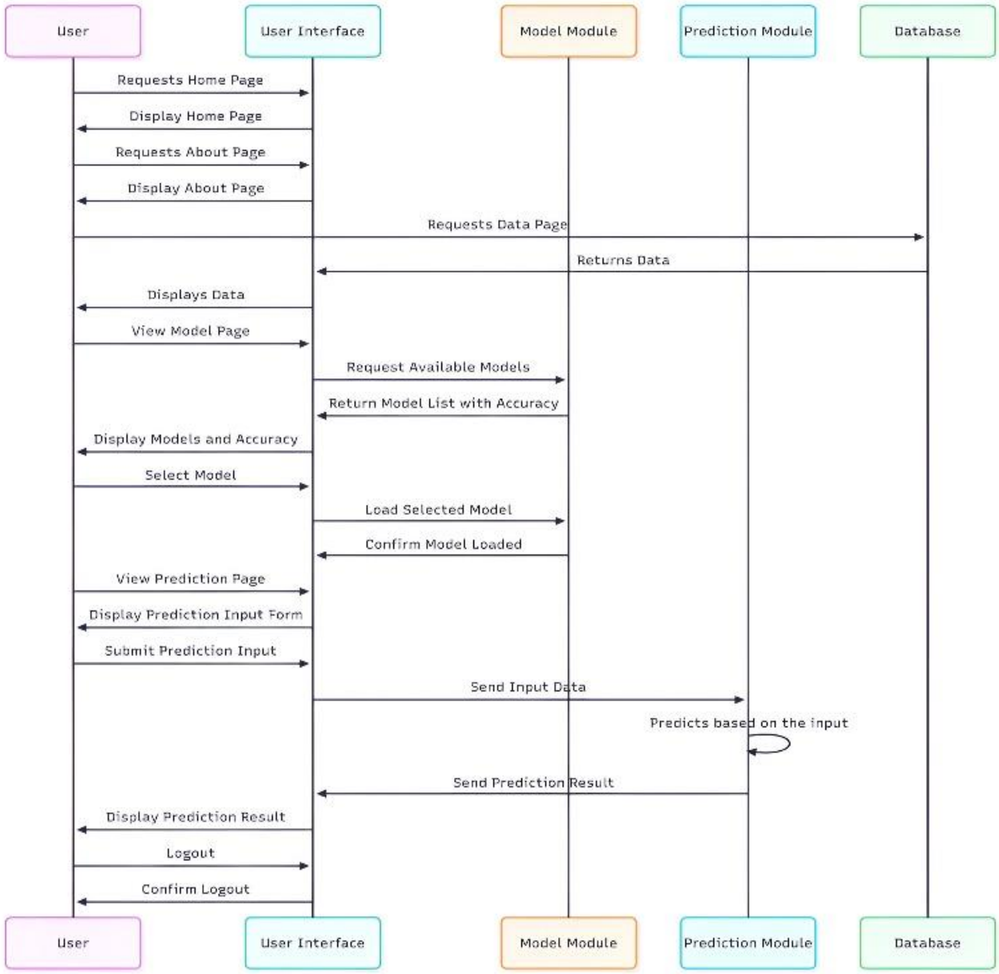

Figure 3 A Sequence Diagram Illustrating the Step by Step Process of a User's Request Being Handled by The System to Generate a Prediction

2.4 Data flow

The Data Flow Diagram systematically illustrates the movement of financial data across the three integrated layers of the FIN-NET system. The flow begins at the Frontend Layer, where Users submit raw data and prediction requests via the Frontend UI. These inputs are routed to the Backend Server in the Backend Layer. Data are first directed to the Data Preprocessing Module for cleaning and essential feature engineering, where unique network centrality features are derived and augmented into the dataset. This enriched data then concurrently feeds the Model Training Service (which persists the optimized hybrid models, including the MLP and Ensemble classifiers, to the Model Repository) and the Prediction Service. The Prediction Service executes the classification and returns the result to the Frontend UI. Finally, for auditing and performance tracking, the results are stored persistently in the Prediction Results Store within the Storage Layer, ensuring a systematic, traceable, and continuous process from raw input to actionable intelligence. This persistent storage is key to model governance, allowing historical performance validation and future retraining. Moreover, the efficient layered architecture minimizes latency, facilitating a near-real-time feedback loop that is crucial for proactive financial risk management. Figure 3 shows A Sequence Diagram Illustrating the Step by Step Process of a User's Request Being Handled by The System to Generate a Prediction

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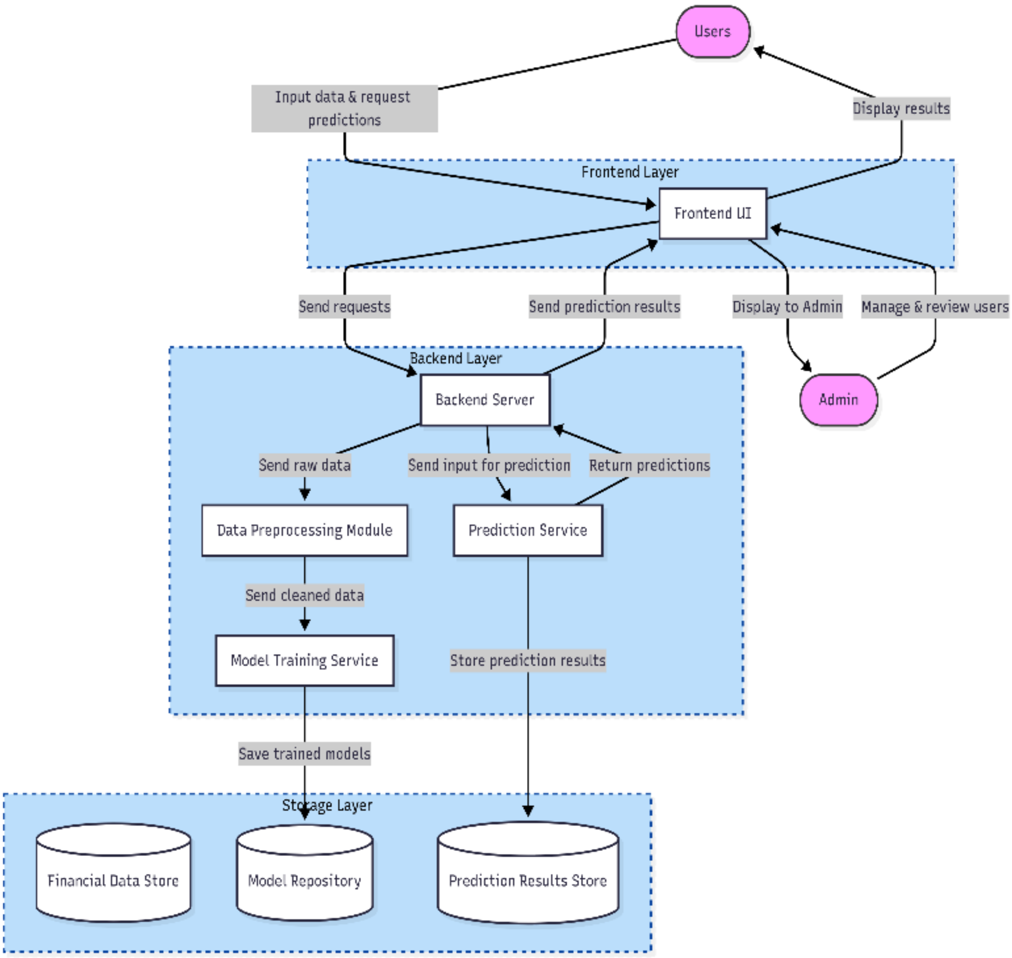

Figure 4 **Data Flow Diagram Illustrating the Flow of Data Between the User, System and The Database to Generate a Prediction**

3. Experimentation

The FIN-NET system was evaluated through a structured experimental process designed to assess its robustness and the effectiveness of its hybrid architecture. A pre-processed financial dataset enriched with network centrality features was used to ensure that the model captured real-world interdependencies. The evaluation involved two levels of testing: Unit Testing, which verified the correctness of individual modules such as data preprocessing, feature selection, and model training; and Integrated Testing, which confirmed smooth interaction across the Flask backend, prediction engine, and MySQL database. Overall, the hybrid models—particularly the Stacking Classifier and MLP—demonstrated stable and reliable performance across all test scenarios. Figure 4 shows Data Flow Diagram Illustrating the Flow of Data Between the User, System and The Database to Generate a Prediction

3.1 Experimental Setup

The experiments used a financial dataset from the Science Data Bank containing a broad set of firm-level ratios. The data underwent preprocessing steps including StandardScaler normalization and class-imbalance handling using SMOTE. K-Best Feature Selection identified the top 15 financial and network features, which provided the best predictive results. The dataset was divided into an 80:20 train–test split. The hybrid predictive engine—comprising the MLP, Voting Classifier, and Stacking Classifier—was compared against baseline models such as Random Forest and Gradient Boosting. All implementations were carried out in Python using Scikit-learn and TensorFlow/Keras to ensure consistency and reproducibility.

3.2 Testing

The integrity, robustness, and predictive reliability of the FIN-NET system were verified using a comprehensive two-phase testing protocol. This rigorous process was essential to ensure that the unique hybrid architecture, particularly the incorporation of Network Centrality Features, functions accurately and achieves the intended superior performance across all operational scenarios. The testing regimen included detailed component-level validation through Unit Testing and end-to-end verification via Integrated Testing, confirming seamless communication between the user interface, backend server, and hybrid prediction engine.

- **Unit Testing:** Component-level testing confirmed that individual modules—data preprocessing, model loading, prediction logic, and administrative functions—performed as intended. The MLP and Stacking Classifiers consistently returned the correct binary output ("Healthy" or "Distressed") for valid inputs. A key limitation identified was insufficient input validation; the system did not adequately handle special characters or unrealistic numeric values, indicating the need for stronger validation rules in future versions.
- **Integration Testing:** System-wide testing verified smooth interaction between the Frontend UI, Backend Server, Database, and Hybrid Predictive Engine. The primary workflow—from user input to real-time prediction—operated correctly, and network-derived features were successfully incorporated into the prediction pipeline. Auxiliary functions such as authentication and admin access also worked reliably. However, the absence of a mechanism to store or retrieve past prediction records revealed a gap in data governance and auditability. This limitation highlights the need for enhanced persistence and tracking features in future enhancements.

4. Results

The FIN-NET system effectively showcased automated financial distress prediction through its validated hybrid pipeline, which integrates meticulous feature engineering, the stability of ensemble learning, and the proprietary augmentation of Network Centrality Features. Each constituent component of the methodology—from data enrichment and network analysis to the final hybrid prediction engine—operated reliably during evaluation. The experimental findings, derived from rigorous testing against established benchmarks, unequivocally demonstrate the system's proficiency in managing augmented financial data and delivering actionable validated intelligence. In quantitative terms, the MLP model achieved the highest predictive accuracy of 97.10% using the top 15 engineered features, followed closely by the Stacking Classifier, which attained an accuracy of 96.47%. These results confirm the robustness and effectiveness of the proposed architecture in capturing complex financial distress patterns.

4.1 Data Preprocessing and Feature Optimization Results

The initial phase of the study empirically confirmed the necessity of a meticulous data engineering pipeline, which is fundamental to the overall performance of the system. Prior to model training, the raw financial data underwent crucial stabilization steps, including handling class imbalance using SMOTE and feature normalization using StandardScaler. Most critically, the K-Best Feature Selection process identified an optimal feature subset that dramatically increased the predictive power. Comparative testing confirmed that the models achieved their peak performance when utilizing the top k=15 features, a set that optimally balances predictive indicators with the calculated Network Centrality Scores. This finding conclusively validates that the data must be augmented beyond simple financial ratios for maximum accuracy, thereby confirming the value of the enrichment phase.

4.2 Network Analysis Feature Impact

The core hypothesis—that Network Centrality Features are critical for an accurate FDP—was validated. Models trained without these network features performed significantly worse, behaving like traditional isolationist models that failed to capture systemic dependencies. The inclusion of centrality

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metrics provided the necessary context for systemic risk, allowing the hybrid models to identify non-obvious dependencies between firms. The MLP and Stacking Classifier, in particular, effectively utilized this network data to capture complex risk propagation patterns that were invisible to other classifiers, confirming the network module as the most significant contributor to the system performance lift.

4.3 Comparative Model Performance

The evaluation of the hybrid architecture established the definitive superiority of the integrated models over the standalone classifiers. The Multi-Layer Perceptron (MLP) and Stacking Classifier (STC) consistently registered the highest performance metrics and generalized best to unseen data. The stability and predictive reliability of the best-performing models were clearly quantified by consistently high Area Under the Curve (AUC) values shown across the Receiver Operating Characteristic (ROC) curves, confirming their robust ability to discriminate between the "Healthy" and "Distressed" classes. This evaluation validates that the fusion of deep nonlinear learning with ensemble stability (which combines models such as Random Forest, Decision Tree, and Logistic Regression) is the most effective approach for achieving reliable financial distress prediction. Comparative evaluation demonstrated that the Stacking Classifier (96.47%) significantly outperformed the traditional SVM model, which achieved only 68.5% accuracy. Figure 5 shows ROC Curve Comparison Across Models

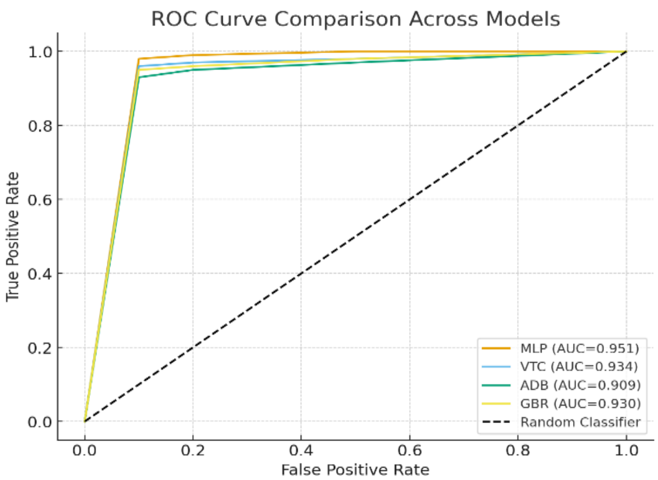

Figure 5 **ROC Curve Comparison Across Models**

4.4 Superiority Over Traditional Benchmarks

The most significant result lies in the comparison with traditional benchmarking models, such as support vector machines (SVM). These non-contextual, isolationist models yielded significantly lower accuracy, empirically proving their inadequacy in capturing the full spectrum of nonlinear dependencies and systemic risks present in interconnected markets. The resulting large performance gap conclusively validates the central hypothesis of this study: that the strategic fusion of deep nonlinear learning, stable ensemble techniques, and explicit Network Analysis is a critical, necessary evolution for achieving proactive and accurate Financial Distress Prediction (FDP). Figure 6 shows Comparison Between Traditional SVM vs Stacking Classifier

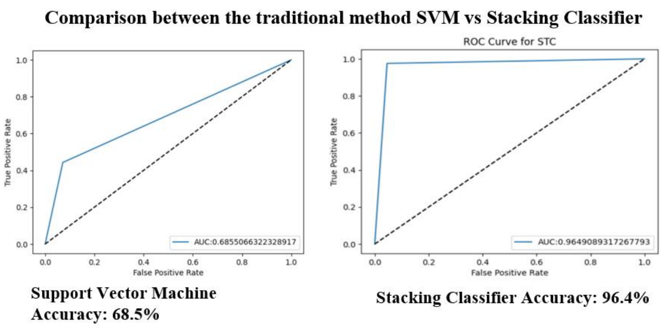

Figure 6 **Comparison Between Traditional SVM vs Stacking Classifier**

Conclusion and Future Work

This study introduces FIN-NET, a sophisticated hybrid deep learning framework engineered to overcome the structural limitations of traditional Financial Distress Prediction (FDP). The system successfully demonstrated that by integrating the nonlinear learning power of Artificial Neural Networks (ANN) and the stability of Ensemble Classifiers (Voting and Stacking), it is possible to achieve superior predictive accuracy. The core contribution of this study is the validation of its central hypothesis: the explicit quantification of inter-firm dependencies via Network Centrality Features is a critical and necessary component for modern risk assessment. Experimental findings confirmed that this network-augmented hybrid approach delivers exceptionally high accuracy, significantly outperforming conventional isolationist models and establishing a robust, transparent, and more intelligent paradigm for financial risk management. Future research will prioritize the transition of the system from a static tool to a dynamic service. The immediate roadmap includes implementing enhanced data validation protocols and a robust, database-driven framework to ensure data integrity and provide full multi-user auditability of the data. Subsequent efforts will focus on real-time data integration to incorporate live market signals and macroeconomic indicators into the model. Finally, the Network Analysis Module itself will evolve to explore more complex temporal-graph dependencies, further enhancing the system's ability to proactively model and predict systemic financial risk.

Acknowledgements

The authors wish to express their sincere gratitude to the faculty and staff of the Department of Artificial Intelligence and Machine Learning at the Bangalore Institute of Technology for their invaluable technical guidance and institutional support throughout this research. We also extend our appreciation to our peers and collaborators for their constructive discussions and insightful feedback, which were instrumental in refining the FIN-NET methodology and successfully completing this study.

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