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Research Article

Hybrid Fuzzy-XGBoost Framework for Predicting Business Economic Performance and Assessing Financial Stability

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Abstract *– Assessing financial stability and enhancing business economic performance are crucial for sustainable growth, sound decision-making, and increased shareholder value in today's unstable economic climate, where businesses face an increasing risk of financial distress and bankruptcy due to unfavourable internal and external factors. In order to reduce redundant, noisy, and irrelevant features while successfully addressing class imbalance and enhancing data quality, this study suggests a machine learning-based framework that combines data normalisation, SMOTE oversampling, and feature selection. Using the enterprise financial network dataset, a fuzzy XGB classifier is created to assess business economic performance and financial stability. Standard performance criteria, including as accuracy, precision, recall, and F1-score, are used to assess the suggested Fuzzy XGB framework. The Fuzzy XGB classifier has a 95.08% classification accuracy, 93.48% precision, 91.76% recall, and an F1-score of 95.93%, according to experimental results, demonstrating its superior predictive ability and classification efficacy. The results verify that a strong and dependable framework for evaluating financial stability and improving business economic performance is provided by the combination of sophisticated data preprocessing methods, feature selection, and the Fuzzy XGB classifier. This framework facilitates the early detection of financially vulnerable organisations and supports strategic financial planning and sustainable organisational growth in dynamic economic conditions.*

Keywords— *Convolutional Neural Networks (CNNs), Synthetic Minority Over-sampling Technique (SMOTE), Graph Neural Networks (GNNs).*

I. INTRODUCTION

Numerous businesses' financial economies are obviously impacted by different management styles in today's society. Developing businesses economically is a crucial pillar for society's continuous advancement. The field of business administration is one of the most applied branches of management[1]. Industrial and commercial management plays a crucial role in our government today. The existing state of market finance can be significantly improved by implementing a standardised system for managing the market economy, which can have a positive impact on the administration of industrial and commercial functions.

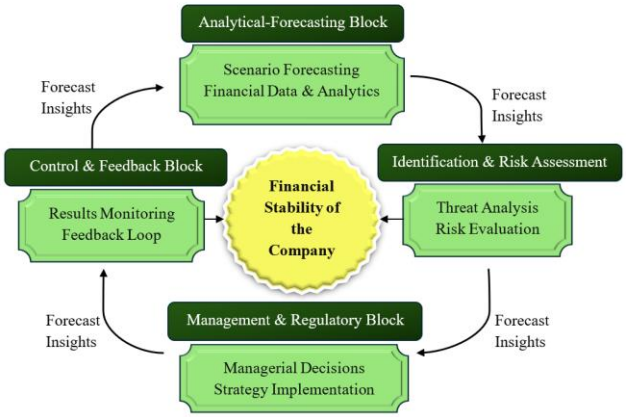


Fig1. Integrating Financial Forecasting Into Processes Of Financial Risk Management

Financial stability, risk management and financial forecasting are all interconnected parts of a single management mechanism, as can be seen from the interpretation of their relationship. This underscores the necessity for more systematization and practical organization[2]. Fig.1 depicts the proposed conceptual model for financial risk management that incorporates financial forecasting, which is based on analytical observations and theoretical generalisations. A company's financial stability is the most important part of its financial condition since it shows the level of investment in the company and represents the largest and most concentrated margin of safety[3]. This describes the enterprise's solvency and is part of the financial condition. When a business is financially self-sufficient and uses its own funds or borrows from financial institutions to purchase its current and noncurrent assets, costs, cash, and receivables, it is considered financially stable[4].

A development company's independence from outside partners and the reasonableness of financing assets requires constant vigilance over the company's financial stability, which management must attend to throughout the duration of the business. The following is the outline of the article. A literature study on evaluating financial stability and business economic performance is presented in the literature review section. The suggested theoretical framework is introduced in the Methodology section. Research results is a simple way to describe the findings. 'Conclusions' discusses the final conclusions.

II. RELATED WORKS

The effectiveness of enterprise stability controlling can be enhanced by creating a set of indicators that measure the dynamics of financial and economic enterprise stability at the economic system exit. The interconnectedness of sustainability trends is one of the most important current developments in business assessment and performance[5]. Companies, governments, and financial organisations throughout the world are launching new projects that challenge the long-held belief that financial and non-financial reporting are only very closely related. The generative capabilities of VAEs and GANs have driven their rise to prominence in financial applications. Among VAEs' many useful applications are anomaly detection, which includes the real-time identification of fraudulent transactions[6]. Utilising GANs which comprise a generator and discriminator network has allowed for the simulation of market situations, yielding useful insights for scenario analysis and stress testing[7]. These algorithms help us understand financial systems better by simulating relationships that are too complicated for more conventional methods to capture.

For financial data and business performance forecasts, LSTM networks have proven to be the most effective deep learning architecture. This is mainly because of their strengths in time-series modelling. As a compromise between precision and efficiency, they verified the structure's efficacy in managing financial time-series data, especially in cases of uncertainty and information asymmetry[8]. They anticipated retail businesses' monthly sales data using a GRU structure, which takes into account the fact that different variables

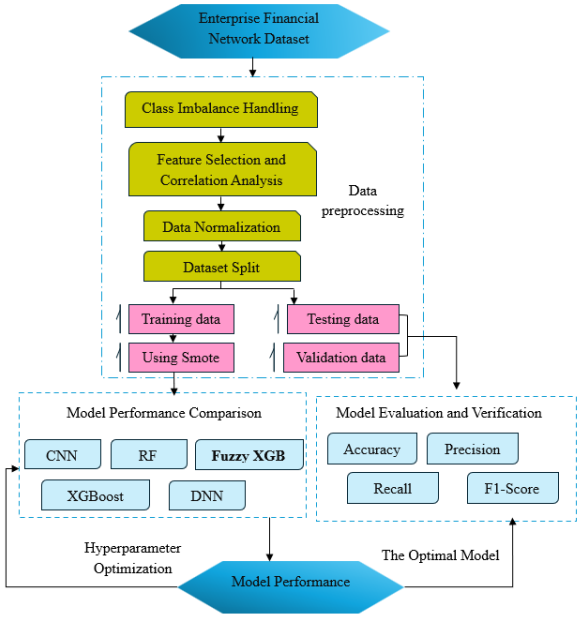
have diverse impacts on company outcomes[9]. One effective framework for representing complex systems' relational and topological information is GNNs. Because of the interconnected nature of banks, assets, and ownership structures, graphs encoding the pathways through which systemic risk can spread are an inevitable byproduct of the financial system[10]. To better detect clusters of systemic risk in stock correlation graphs and provide early warning of market stress situations, they created a framework based on GAT. These examples highlight that in contrast to conventional regression-based approaches, graph-based architectures can expose hidden structural dependencies.

A growing number of investigators are utilising the DNN technique. A NN model that excels at handling time series information, CNN has been progressively utilised with promising outcomes in the financial sector, due to the fact that financial data exhibits the properties of standard time series[11]. Consequently, trying and studying the way of employing a NN model to handle financial data is an essential necessity[12]. Because financial crises can take many forms, fitting a linear function to the prediction curve is an exercise in futility. As a result, financial crisis prediction curves are inherently nonlinear and are intimately related to DL. GRU and LSTM models have been used extensively in many study and are well-known in financial time series analysis[13]. Daily, weekly, and monthly price data are just some of the time scales that these models are used on, and to further improve prediction accuracy, they are often combined with attention mechanisms and CNNs. Statistical methods such as cross-correlation have been the backbone of classic stock network construction methodologies, but they could not account for the nonlinear, complicated interactions present in financial data.

Performance Evaluation of Businesses and Evaluation of Their Financial Stability Using the Fuzzy XGB Model. Integrating the Fuzzy C means algorithm and the XGBoost classifier, the proposed Fuzzy XGB classifier was created to increase classification performance. The proposed Fuzzy XGB classifier's end result is an evaluation of financial stability and the identification of company economic performance.

III. METHODLOGY

Business risk assessment is an important factor in ensuring a company's financial stability, and this study aims to discover the essential patterns that define its aspects. Various economic risks, methods for analysing and assessing risks, and strategies for mitigating risks are all thoroughly examined. The significance of creating an integrated risk assessment technique is shown by the findings.



Overall Architecture Of The Proposed Model

This study primarily used the Fuzzy XGB model for evaluating financial stability and business economic performance[14]. The figure shows the experimental process. The four steps are as follows: preprocessing the data,

selecting features, building the model, training it, and finally, predicting and evaluating its performance. Fig.2 shows the overall workflow.

Dataset Description

Research and analysis about financial risk contagion within interconnected enterprise systems can be aided by this dataset[15]. It captures the internal financial health of businesses as well as their external business links through modelling a network of 2,934 enterprises and 9,000 directed relationships.

This file is a combined dataset that shows the inter-organizational relationships and enterprise-level financial features. Row after row details the relationship between two businesses, merging:

The financial and risk-related data of the target and source businesses.

Their relationship's nature, intensity and frequency.

A binary label that indicates both connected parties' danger of bankruptcy.

Data Preprocessing

Class Imbalance Handling

SMOTE or the Synthetic Minority Oversampling Technique, was used to create fictitious examples of failed companies[16]. Interpolating between current minority class samples and their k-nearest neighbours in accordance with equation (1)allows SMOTE to generate synthetic examples.

$$w_{synthetic} = w_j + \mu \times \left(w_{mm} - w_j\right) \quad (1)$$

where w_j stands for an initial instance of the minority class, w_{mm} for one of its k-nearest neighbours and μ for a random integer between $0\ and\ 1$.

Data Normalization

In order to avoid features with bigger numerical ranges from dominating the learning process and to create uniform scaling across multiple measures, all preserved financial features were normalised after feature selection. Equation (2) was used to apply Min-Max normalisation, which transformed all feature values to a uniform scale between $0\ and\ 1$.

$$w_{normalized} = (w - w_{min})/(w_{max} - w_{min}) \quad (2)$$

where w is the initial value of the feature, w_{min} is the lowest value of the feature in the dataset and w_{max} is the highest value.

Feature Selection

The goal of the feature selection strategy (FS) is to extract useful features from an enterprise financial network dataset by eliminating superfluous, duplicate or noisy features. The class labels are represented by $Z = \{z_1, \dots, z_m\}$, where m is the number of enterprises and $z_j \in \{0,1\}, j = 1, \dots, m$ is found in one of the two categories d_1 non-financial distress or $d_2$financial distress[17]. Multiple characteristics w_{ji} , where $i = 1, \dots, c$, characterise every enterprise. Equation (3) displays w_{ji} that are suppose are realisations of characteristics W_i that can be arranged in order of importance.

$$EJ = \left(W_{\pi(1)}, \dots, W_{\pi(c)}\right) \quad (3)$$

where the new descending index of feature W_j is denoted by $\pi\ (i), where\ i\ =\ 1, 2, \dots, c.$

Group - Filter techniques presume total autonomy between the model and the data. In this instance, attributes are chosen according to their performance in several statistical assessments, establishing their relationship with the outcome variable.

i. A standardised effect size for comparing the means of two groups financially distressed businesses and non-financially distressed businesses is Cohen's D (ChD) coefficient. Equation (4) defines Cohen's D.

$$ChD = \left| \frac{\bar{W}_{w\epsilon d_1 i} - \bar{W}_{w\epsilon d_2 i}}{\sqrt{\frac{\sigma^2_{w\epsilon d_1 i} + \sigma^2_{w\epsilon d_2 i}}{2}}} \right| \quad (4)$$

Model Training

The suggested Fuzzy XGB classifier is used to detect the anomaly class and the normal class using the reduced features after dimensionality reduction. The suggested Fuzzy XGB classifier combines the best features of both the XGBoost and fuzzy c means classifiers[18]. These include the XGBoost classifier and the fuzzy c means classifier employ gradient boosters to complete the classification process.

Mathematical description of the Fuzzy-Cmeans classifier

This section provides a concise overview of the Fuzzy C means classifier. The Classifier is fed features from the Feature Vector Space $G = G_g \; for \; g = 1 \; to \; L$. Fuzzy c means creates classifications of items into different fuzzy clusters by treating the features as objects. Fuzzy logic defines the cluster centers or centroids for fuzzy clustering. In order to divide up the K-dimensional characteristics, the fuzzy C-means method establishes d fuzzy clusters. Fuzzy clustering involves defining a fuzzy matrix K with L rows and d columns. In the fuzz matrix K, each element is represented as K_{ji}, which is the degree of association or the membership function. The following equation (5) & (6) describes the K_{ji} membership function.

$$K_{ji} \epsilon (0,1), j = 1 \; to \; l, i = 1 \; to \; c \quad (5)$$

$$\sum_{i=1}^{c} K_{ji} = 1 \; for \; j = 1 \; to \; L \quad (6)$$

The clustering objective function denoted as the minimisation function is presented in equations (7) & (8).

$$P_z = \sum_{j=1}^{L} K_{ji} \sum_{i=1}^{c} K_{ji}^{z} r_{ji} \quad (7)$$

$$0 < \sum_{j=1}^{L} K_{ji} \leq 1 < L \; for \; i = 1 \; to \; c \quad (8)$$

In order to divide up the K-dimensional characteristics, the fuzzy C-means method establishes d fuzzy clusters. Fuzzy clustering involves defining a fuzzy matrix K with L rows and d columns. The membership function or degree of association is defined as K_{ji} for each entry of the fuzz matrix L.

Mathematical description of the XGBoost classifier

Using the objective function specification, the primary goal of the training procedure is to identify the most appropriate training parameters. All aspects of the model's performance are assessed using the objective function. Two main components make up the objective function used for training. The first component is the training loss function, and the second is the training process regularisation parameter. The training model's goal function is now defined by equation (9).

$$PA(\theta) = K(\theta) + Q(\theta) \quad (9)$$

$Q(\theta)$ stands for the regularisation loss function, and $K(\theta)$ stands for the training loss function. Training the XGBooster is defined by

the training loss function. In addition to preventing overfitting, the regularisation term helps the model train complex features. Consequently, the regularisation component contributes to preserving effective training outcomes. Thus, the XGBoost classifier's goal is considered to be the second order degree of Taylor's series. Equation (10) expands the objective function for the time step t from the second order Taylor series.

$$PA(\theta)^{s} = \sum_{j=1}^{l}\left[h_j q_s(pi) + \frac{1}{2} g_j q_s^2(pi)\right] + Q(q_s) \quad (10)$$

The inputs are h_j & g_j. The prediction output is determined by the XGBoost algorithm using the aforementioned objective. Through the regularisation term, the loss functions are meticulously controlled. Equation (11) can be used to formulate the XGBoost tree.

$$= t_{b(o)}^{\,q_s(pi)} \quad (11)$$

Leaf scores are computed for each tree using the function b, where t is the leaf score. Here is equation (12) for calculating the XGBoost leaf node complexity.

$$Q(q_s) = \beta W + \frac{1}{2}\alpha \sum_{k=1}^{K} x_1^2 \quad (12)$$

The total number of leaf nodes is defined by$K$ in the equation. The regularisation, leaf score, and goal function are computed at each score level to build the XGBoost tree structure. After determining the gain, the node is divided into two parts: the left half and the right half. If the gain value is less than the regularisation, the branch is dropped. One other name for this procedure is tree pruning. The XGBoost is quite good at data classification because it follows all the steps.

Developing BEP and AFS using integrated Fuzzy XGB classifier

This study constructs the BEP and AFS framework by combining the XGBoost and Fuzzy classifiers. The following phases outline the complete process of developing BEP and AFS:

Step 1: the features that will be reduced in dimensionality will be utilised as the inputs for training. The XGBoost classifier and the Fuzzy C means receive their inputs independently.

Step 2: Model training with both the XGBoost classifier and the Fuzzy C means accomplishes the classification.

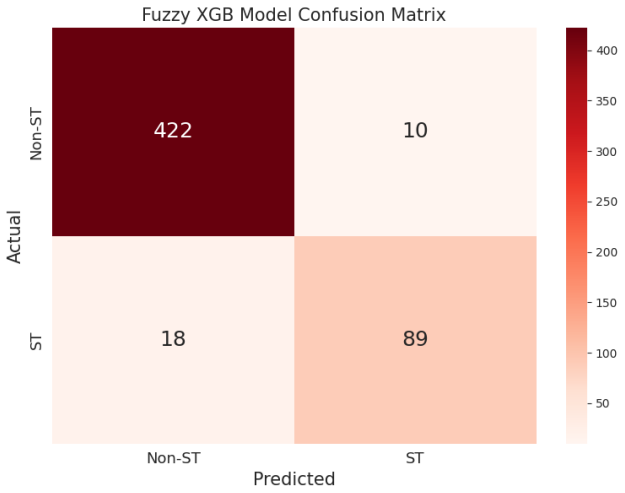
Step 3: In order to classify data, classifiers minimise the objective function.

Step 4: Every test input causes the classifier to generate two outputs, one for each class, based on the training data. such as the typical class and the outlier class.

Step 5: As a result of training the model, a binary class will be produced. A normal class is represented by 0 and the presence of an anomaly is represented by 1.

IV. RESULT AND DISCUSSION

The task of evaluating and predicting the degree of financial and economic enterprise stability through the establishment of integrated indicators is addressed in this paper. There is a severe need to reflect about this unpredictability because many businesses currently function in a fluctuating external environment. It considers the rule is feasible and essential to apply the tools of mathematical statistics and probability theory to assess, analyse and forecast the enterprise's sustainability in crisis conditions.



Fuzzy XGB Model Confusion Matrix

Fig.3 shows the results of the Fuzzy XGB model's confusion matrices. The confusion matrix displays the total number of correct and incorrect classifications for ST and non-ST categories. The model's accuracy of 95.08% indicates that it performed adequately. Nevertheless, when it came to predicting ST firms in particular, it the highest accuracy rate. There were 18 incorrect predictions out of 107 real ST sequence data points. It seems that the Fuzzy XGB could be the only tool needed to get the best results.

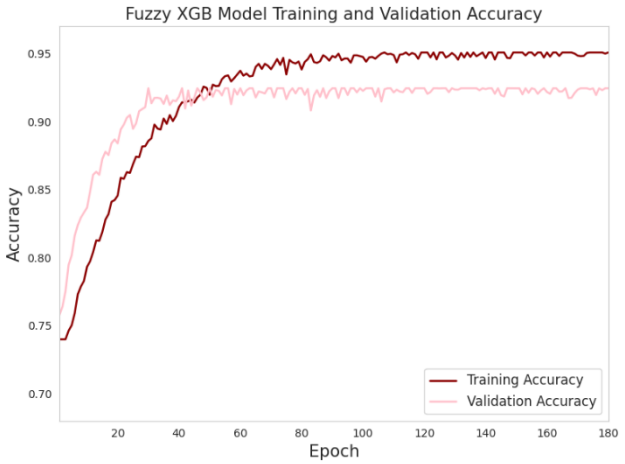


Fig. 1. Fuzzy XGB Model Training and Validation Accuracy

The Fuzzy XGB model outperformed all of the other structures in terms of training accuracy (0.9508) and validation accuracy (0.9245) after 180 training epochs. The Fuzzy XGB model shows excellent stability and convergence in the training and validation accuracy processes as shown in Fig.4.

performance Comparison

Models	Accuracy	Precision	Recall	F1-Score
CNN	87.29	85.86	83.22	87.79
RF	78.46	76.53	74.92	78.69
Fuzzy XGB	95.08	93.48	91.76	95.93
XGBoost	76.17	74.82	72.36	76.82
DNN	90.32	88.69	86.81	90.68

Table 1 compares the five machine learning models CNN, RF, Fuzzy XGB, XGBoost and DNN based on their performance as measured by Accuracy, Precision, Recall and F1-Score. Fuzzy XGB outperforms all other models in terms of overall performance, with the highest Accuracy (95.08%), Recall (91.76%), Precision (93.48%) and F1-Score (95.93%). Although the XGBoost model did not perform better than any of the others, with the lowest Precision (74.82%), Recall (72.36%), Accuracy (76.17%) and F1-Score (76.82%).

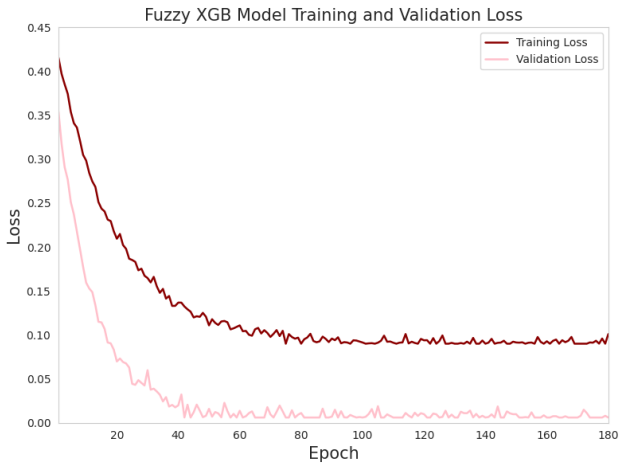


Fig. 2. Fuzzy XGB Model Training and Validation Loss

Experiments on the proposed Fuzzy XGB model revealed that, after 180 training epochs, it achieved the best training loss of 0.09 and validation loss of 0.06. The loss value will decrease as the epoch increases. Fig.5 loss value

trend figure illustrates the Fuzzy XGB model's impressive convergence and stability throughout the training and validation loss processes.

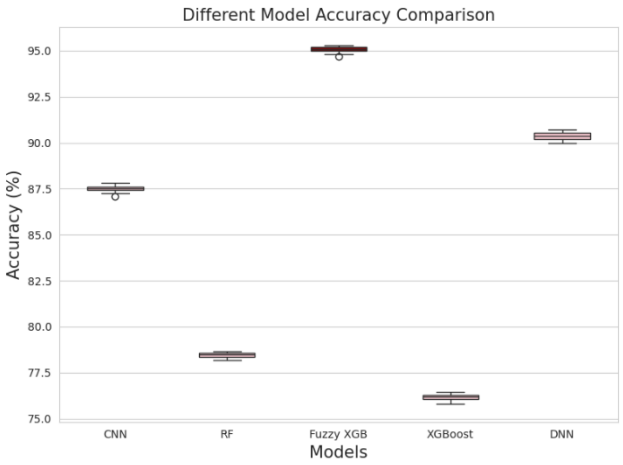


Fig. 3. Different Model Accuracy Comparison

A comparison of the five models' accuracy is displayed in Fig.6. The models include CNN, RF, Fuzzy XGB, XGBoost and DNN. The proposed Fuzzy XGB model outperforms competing models and achieves a respectable 95.08% accuracy rate. A poor accuracy value of 76.17% was produced by the XGBoost model.

V. CONCLUSION

Assessing Financial Stability is crucial for guaranteeing sustainable growth and enhancing Business Economic Performance since financial stability is one of the most important factors influencing a company's long-term viability and competitiveness. Profitability is still the main goal of any business, even though business liquidity is essential for preserving operational continuity. If an organization has a lot of debt and liabilities, it may still have financial instability, which raises the possibility of financial crisis and bankruptcy. In order to overcome these difficulties, this study integrates data normalisation, suitable data preprocessing and feature selection to create a machine learning-based framework for evaluating financial stability and business economic performance. While feature selection eliminates unnecessary, redundant, and noisy variables to increase model efficiency and forecast accuracy, data normalisation and efficient preprocessing are essential for managing enterprise financial network datasets. The dataset is used to create the suggested Fuzzy XGB framework, which uses a Fuzzy XGB classifier for the classification task. The model's efficacy is assessed by conventional metrics such as accuracy, precision, recall, and F1-score. According to experimental results, the suggested Fuzzy XGB classifier achieves 95.08% accuracy, 93.48% precision,91.76% recall and F1-score of 95.93%, demonstrating its efficacy as a trustworthy decision-support model for evaluating financial stability and improving business economic performance.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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