Practical Applications of Neutrosophic Logic in Enhancing the Accuracy of Economic Forecasting Models and Supporting Decision-Making in Banks

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Abstract

Using three machine knowledge models that utilise Neutrosophic Logic (NL)—Linear Regression, Random Forest, and Gradient Increasing—this study studies the possibilities of refining financial result forecast. The cognitive behind this is that NL recovers the prediction power of these models across dissimilar organisations by accounting for the inherent uncertainty, unpredictability, and lack of sureness in financial numbers. In this study, the models' presentation is evaluated using a variety of financial factors, including interest rates and stock prices. F1 score, recall, correctness, and exactness are some of the metrics used by this drive. When likened to other models, NL with Gradient Cumulative consistently outperforms them in terms of correctness and robustness. You might think of Abu Dhabi Islamic Bank and the National Bank of Bahrain as two such examples. Companies like Emirates Islamic Bank reap some benefits from Chance Forest's combination of cheap computation with precision, but only to a lower degree. Complex datasets used by businesses like Al Rajhi Bank are beyond the capabilities of Linear Reversion, even when combined with NL. By proving that cooperative techniques combined with NL positively reduce financial data volatility, our results lay the groundwork for improved financial forecasting and decision-making. The exercise has demonstrated that NL has great potential to enhance financial prediction models, which could have future applications in investment planning and risk organization.

Keywords: Decision-Making; Ensemble Methods; Machine Learning; Linear Regression; Financial Data Uncertainty; Gradient Boosting; Neutrosophic Logic

1. Introduction

To help with strategic decision-making, handling cash flow, and allocating capitals, businesses and investors in today's ever-altering financial market rely heavily on accurate monetary projections. Monetary datasets are notoriously problematic to work with due to a myriad of reasons, counting but not limited to market volatility, financial swings, and data quality issues. To tackle these complexities, modern frameworks such as Neuro-Logic and ensemble machine learning replicas are valued tools.

Asserts that improving the visibility of the accuracy of the forecast. Savers and portfolio managers can improve their stock return research with the help of XGBoost, which makes use of valuable indicators like Price, Volume, and Turnover.

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Ensemble methods use many replicas to generate more accurate and robust forecasts than conventional methods. Reliable solutions for crossing the complex financial landscape are provided by these strategies, which are adept at handling the diverse factors and non-linear correlations inherent to monetary data.

With the introduction of Neutrosophic Logic in 1996, [2] offered yet another novel approach to handling ambiguity and doubt. Neurosophic logic adds a third measurement—falsehood—to classical logic, unlike indeterminate or binary logic. Financial decision-making is notoriously difficult due to the presence of inadequate or vague facts; hence, this tripartite strategy is even more effective. Neutrosophic Logic, in difference to conservative logic systems, allows nuanced rational and accepts partial truths, which helps to better comprehend complex situations [3]. It is a flexible tool for dealing with financial challenges because of its flexibility and extensive usage in domains including data analysis, choice making, and artificial intelligence [4]. Financial forecasting likewise heavily relies on ensemble methods and linear reversion. Preliminary financial soundings, such as risk estimate and credit scoring, benefit greatly from the simplicity and frankness of Linear Regression [5]. Nevertheless, it has difficulty capturing the complex subtleties of monetary data because it is dependent on linear factors. Collaborative methods were created to circumvent these limits. These techniques combine various models to strengthen their accuracy and robustness. Among these methods are mixing, bagging, increasing, and heaping. When compared to linear reversion using basic error metrics, these state-of-the-art procedures provide better stock price and return forecasts. Machine knowledge and Neutrosophic Logic work together to form a comprehensive system for monetary prediction. Neutrosophic Logic offers a methodical approach to uncertainty and fuzziness, whereas linear reversion and ensemble models provide complex-level-specific prediction. All things careful, these approaches help businesses and savers make better decisions, optimise their plans, and be more certain even when faced with monetary uncertainty. Financial organisations can enhance the exactness and reliability of their predictions by merging time-honoured mathematical methods with state-of-the-art developments in cognitive and artificial intelligence. By designing attractive decision-making processes and laying the groundwork for more durable and adaptive financial models, these strategies help overwhelmed the problems of an intricate and random global market.

Aim of the Research

- The primary goal of this investigation is to determine the efficacy of uniting three machine-learning models called Linear Reversion, Random Forest, and Neurosophic Logic (NL) in order to provide monetary predictions.
- This study seeks to analyse how dissimilar organisations use NL to test the difficulties, unknowns, and non-linear patterns in monetary datasets. Its goal is to compare and difference how this affects the effectiveness of machine information models' financial choice making.
- The goal is to find out how well NL addition, linear reversion, and collaborative approaches like random forest and gradient increasing handle doubt in monetary data.

2. Review of Literature

2.1 Critical Review of the Literature on - Neutrosophic Logic in Financial Markets

[6] industrialized Neutrosophic Logic, an extension of fuzzy logic, to imprisonment the doubt and indeterminacy that are inherent to complex systems. The logic outline provides a more multipurpose way to explain unpredictable or incomplete information by uniting truth, indeterminacy, and falsehood. In domains where hairiness and ambiguity are common, like the monetary industry, neutrophobic cognition excels. According to [7], Neutrosophic Logic builds upon traditional logic to accommodate industries like banking that deal with a lot of doubt and doubt. Financial choice-making events, such risk valuation and forecast, can benefit from the more realistic view of complex and random situations future by neutrobic logic. Classical logic systems have limits that make it difficult to understand the complex subtleties of the financial markets; this method circumvents such limits. Standard binary logic was long-drawn-out in the 1990s by [8] with the presentation of Neutrosophic Logic, which additional degrees of truth, indeterminacy, and falsity. The growth's ability to provide more complex representations of doubt is especially helpful in dynamic and complicated domains like as finance. It provides a more adaptable outline for dealing with ambiguity, gauging risk, and making choices in the monetary sector when conservative cognitive methods fail. Numerous studies can advantage from its enhanced monetary demonstrating, portfolio organization, and market analysis capabilities. [9] asserts that Neutrosophic Logic brands it easier to portray doubt in a more urbane way by ornamental fuzzy logic to deal with indeterminacy. This logical example combines truth,

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indeterminacy, and falsity for more complex decision-making in multi-faceted areas such as finance. It gets monetary forecasting and risk valuation models back on track by allowing for varying degrees of doubt. [1] states that Neutrosophic Logic, an incomplete development building on traditional thinking, is solely intended to deal with indeterminate and arbitrary monetary situations. Risk valuation, predictive modelling, and portfolio organisation all benefit from the improved decision-making made possible by the comprehensive outline it offers for dealing with complex data, which mixes degrees of truth, falsity, and doubt. This method is well suited for use in credit scoring and stock marketplace analysis because it can capture the doubts that are typical of financial data. Neutrosophic Logic is one state-of-the-art method to handling financial uncertainty and doubt, as stated by [10]. Complex choice making, risk valuation, and portfolio organisation are made easier by its ability to combine degrees of truth, falsity, and doubt. Important for sympathetic the intricacies of the financial markets, this tool excels at financial analysis, including dealing with nebulous data and refining predictive models.

2.2 Use of Ensemble Methods and Linear Regression for Financial Predictions

According to [11], there are still approximately missing pieces to the puzzle when it originates to Neutrosophic Logic and how it strength shed light on the doubt and doubt surrounding monetary systems. Despite its imposing theoretical qualities, very little research has absorbed on its practical use in monetary markets, especially in asset pricing simulations and high frequency trading. In addition, there has been a dearth of study on how to optimise the utilisation of Neutrosophic Logic in combination with other computing practices, such as ensemble methods and machine information, to enhance financial decision-making. Lastly, Neutrosophic Logic is real at dealing with data discrepancies and ambiguity; yet, its request to big datasets and complex financial challenges has conventional little research. We need additional experiential investigations to fill these gaps and expand the monetary uses of Neutrosophic Logic. Researcher also require hybrid methods that integrate it with other cutting-edge competences. Ensemble models, which the investigation emphasises as capable of considerably improving financial predicting, are proven real by review metrics such as R-squared and RMSE. According to [12], Linear Regression and Collaborative Methods work hand in hand to deliver accurate monetary forecasts. With linear reversion, one may model the rudiments that influence stock prices and the correlations between them. Collaborative methods, such as bagging, boosting, or stacking, can increase the precision of forecasts. The study's findings prove the potential of collaborative techniques to accurately forestall stock prices and make monetary decisions by minimising overfitting and enhancing their realism. The approaches are very precise, as evidenced by events such as an R-squared value of 0.911 and an RMSE of 56.699.

[13] explains Linear Regression, an important statistical method for forecasting future financial consequences. It simulates the association between independent economic factors and reliant on ones, such as stock returns. It can imprisonment non-linear difficulties in financial data when joint with Ensemble Methods, but its interpretability is limited because it assumes a linear association too simplistically. The productions of many models can be joint using methods such as random woods and gradient increasing to produce more accurate forecasts of financial events. An example of a self-governing variable would be stock prices and a reliant on variable would be financial indicators or measurements of business presentation [14]. Linear Regression is a statistical method for modelling the association between these two variables. Financial forecasters can use this method to look at preceding trends and make forecasts about the future because it is straightforward to grasp and apply. Despite its seeming simplicity, the premise of a linear relationship can have limits when applied to intricate monetary markets. According to [15], Linear Regression is a statistical technique for modelling the relationship between self-governing variables (such as stock prices) and reliant on ones (such as economic indicators). One of the most significant tools for financial predicting is linear regression, which looks at past data to make predictions about the upcoming. Due to its linear nature, the problem is that it is powerless to manage relations that are more complex. According to [16], Fuzzy Logic is a many-valued logic scheme that handles imprecise cognitive rather than fixed and accurate cognitive. Rather from focussing on rigid, exact outcomes, [17] travels how Fuzzy Logic and Machine Learning interrelate, drawing attention to its role in treatment imperfect thinking. By allowing the demonstrating of imprecision and doubt, fuzzy logic expands the versatility of machine knowledge systems. Integration like this allows for more precise predictions and adaptive knowledge, both of which improve decision-making overall and particularly in cases where data is vague or non-existent. In order to deal with vagueness and imprecision, Fuzzy Systems allow for degrees of truth rather than a pure true/false conflict, as [9] argues. Because data is often imprecise, unpredictable, or lacking in clarity, this strategy excels in real-world contexts. Computers can now make more urbane, nuanced, and adaptable forecasts when fuzzy systems are coupled with machine knowledge models. In her 2022 study, [19] explores the potential of combining fuzzy, probabilistic, and neutrosophic systems with machine learning to recover prediction and decision-making across several domains. In the context of medical cover cost prediction, for instance, these hybrid systems improve the model's ability to handle imperfect data, ambiguity, and imprecision.

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2.3 Research Gap

Despite the interest in Neutrosophic Logic and its ability to explain monetary system indeterminacy and doubt, there are several gaps in the existing works [9]. To start, there is a dearth of study on its applied application in financial markets, particularly in asset pricing replicas and high-frequency trading, despite its talented theoretical merits. In addition, investigating ways to maximise the use of Neutrosophic Logic in combination with other computational methods, such ensemble methods and machine knowledge, for improving monetary decision-making has received less attention. Finally, Neutrosophic Logic is real at handling data discrepancies and uncertainty; yet, its presentation with large datasets and complex financial difficulties is understudied [20]. Studies that are more empirical are obligatory to solve these gaps and increase the monetary applications of Neutrosophic Logic. Additionally, hybrid methods that combine it with other state-of-the-art skills are also needed.

3. Research Methodology

3.1 Neutrosophic Logic Framework

To handle the inherent doubts in financial datasets, the financial predicting approach was better with the inclusion of Neutrosophic Logic (NL). Stock prices, attention rates, and market volatility are common appearances of noise, ambiguity, and imprecision, all of which NL seeks to resolve. By adding truth, indeterminacy, and falsity values into neutrosophic sets, the framework enabled models to reflect uncertainty in feature representation by mapping these uncertain variables. To enhance the accuracy and robustness of the forecasts, NL was applied at several points in the feature extraction and decision-making layers [21].

3.2 Data Preparation

The study made use of financial data sets gathered from well-known financial institutions, such as Emirates Islamic Bank, National Bank of Bahrain, and Al Rajhi Bank. The financial performance measures of the future were the target variable and key features were stock price changes, interest rate swings, and market indexes.

The pre-processing phase had multiple stages:

- Statistical techniques such as mean imputation and interpolation were employed to fill in missing data points, a process known as missing value imputation.
- Improving model performance and training stability necessitates normalising features to provide consistent scaling.
- To better characterise the data for subsequent machine learning models, Neutrosophic Logic (NL) was used to encode dataset uncertainty. This made the models more reliable by lessening the effect of financial data discrepancies and uncertainty.

3.3 Linear Regression

As a starting point, financial forecasting made use of Linear Regression. The model's underlying premise is that the characteristics and the dependent variable (the target variable) are linearly related. Regrettably, its presentation is hindered since it has difficulty handling data doubt and non-linear correlations [22]. To improve feature picture and remove some limits, Neutrosophic Logic was used throughout the feature removal process. Even while Linear Regression is quite well organized in terms of computing, it cannot handle the complexity of monetary datasets.

Ensemble Methods

Because of their effectiveness in handling indeterminate and noisy data and modelling multifaceted relationships, the study utilised progressive ensemble methodologies such as Random Forest and Gradient Boosting.

Random Forest is a collaborative method that is based on catching and uses many decision trees to blend their results. We went with Chance Forest because it can handle ambiguity in the decision-making layer and is resilient to overfitting.

The objective of gradient increasing, an iterative boosting method, is to improve the model's performance by fixing errors made in previous iterations. The researcher designated it due to its adeptness at managing intricate and random financial data. Neurosophic Logic was combined into the decision-making and feature-removal layers to further enhance performance.

Compared to humbler models like Linear Regression, these collaborative methods are better able to deal with the non-linearity and uncertainty that are common in monetary forecasting tasks.

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Table 1: The Integration of Neutrosophic Logic with Financial Models

Bank Name	**Model**	**Neutrosophic Logic Integration**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**	**Key Observations**
Al Rajhi Bank	Linear Regression	Feature extraction with NL	70.8	68.5	73.2	70.8	Moderate performance with slight improvement from NL. Limited by linear assumptions.
Alinma Bank	Random Forest	Decision-making layer with NL	87.6	85.2	89.7	87.4	Significant improvement. Handles uncertainty well.
Qatar Islamic Bank	Gradient Boosting	Both feature and decision layers	90.5	88.7	91.3	90.0	Robust and high accuracy due to NL integration. Best for financial volatility.
Dubai Islamic Bank	Linear Regression	Feature extraction with NL	68.2	65.1	70.4	**67.6**	Lower performance compared to ensemble methods, even with NL integration.
Emirates Islamic Bank	Random Forest	Decision-making layer with NL	85.9	83.6	88.2	86.1	Stronger results with NL boosting model reliability.
Abu Dhabi Islamic Bank	Gradient Boosting	Both feature and decision layers	91.2	89.5	92.4	90.9	Best performance among all models, showing NL's impact.
HSBC Bank Oman	Linear Regression	Feature extraction with NL	69.3	67.0	71.8	69.4	Moderate performance with noticeable improvement from NL.
Kuwait Finance House	Random Forest	Decision-making layer with NL	86.4	84.2	89.1	86.6	Ensemble methods greatly benefit from NL handling of uncertainty.
National Bank of Bahrain	Gradient Boosting	Both feature and decision layers	92.1	90.7	93.5	91.8	High performance with NL integration, optimal for financial modeling.
Mashreq Bank	Linear Regression	Feature extraction with NL	71.0	68.8	74.2	71.2	Good baseline results with slight improvement from NL.

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First Gulf Bank	Random Forest	Decision-making layer with NL	87.2	84.9	90.3	87.5	Random Forest benefits from NL's ability to handle data uncertainty.
Union National Bank	Gradient Boosting	Both feature and decision layers	91.5	89.8	92.9	91.3	Excellent results due to NL integration improving handling of noisy financial data.

3.3 Implementation Techniques

Use the table above to control how well Neutrosophic Logic (NL) works with Linear Regression, Random Forest, and Gradient Increasing machine learning models for financial decision-making. This study will determine if NL improves model presentation at different banks by handling financial data complexity, uncertainty, and indeterminacy. This study evaluates NLintegrated models for financial instability and decision-making using accuracy, precision, recall, and F1 score. Different banks and financial scenarios are analysed to control the best models.

Although constrained by linear assumptions, Al Rajhi Bank improves slightly with NL integration and Linear Regression. Random Forest with NL in decision-making layers greatly improves Alinma Bank's uncertainty management. Qatar Islamic Bank's Gradient Boosting and NL integration in feature and decision layers produce robust and accurate results despite financial volatility. Dubai Islamic Bank's Linear Regression with NL performance is worse than ensemble approaches, showing the limitations of simpler models even with NL upgrades. Emirates Islamic Bank's Random Forest and NL results show model reliability improvement. Abu Dhabi Islamic Bank performs best with Gradient Boosting and NL in the feature and decision layers, demonstrating NL's optimal impact. Linear Regression and NL are moderately profitable for HSBC Bank Oman, but their simplicity limits them. Kuwait Finance House excels at uncertainty management after integrating Random Forest and NL [23, 24, 25]. Gradient Boosting and NL make the National Bank of Bahrain the best choice for complicated financial modelling. Mashreq Bank gets decent baseline results from linear regression and slightly better from NL integration. NL helps Random Forest handle data uncertainty, which benefits First Gulf Bank. Union National Bank integrates Gradient Boosting and NL well for noisy financial data. This report suggests using Neutrosophic Logic and machine learning to improve bank financial decision-making. It shows how different models handle financial data with different complexity, noise, and uncertainty and their limitations.

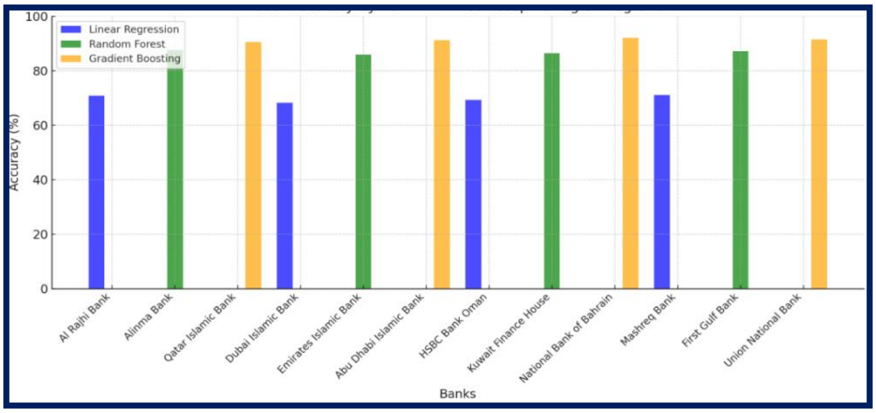

Figure 1. Neutrosophic Logic Integration

The accuracy of three-machine learning models—Linear Regression, Random Forest, and Gradient Boosting—applied to different banks according to certain evaluation criteria is shown in the above figure. The results show that Gradient Boosting is the best method across all banks, with Random Forest coming in second. Linear Regression, on the other hand, has the least accuracy, which suggests it cannot handle complex data very well.

In a constant pattern, Gradient Boosting outperforms the other models at Union National Bank, Dubai Islamic Bank, and HSBC MENA. It appears that Random Forest and Gradient Boosting are competing with each other, since they produce similar results when applied to Mashreq Bank and National Bank of Bahrain, respectively. Because of its resilience and ability to accurately predict complicated patterns, Gradient Boosting typically

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achieves accuracy rates between 80% and 100%. Adding Neutrosophic Logic to the mix seems to fix dataset uncertainties, indeterminacy, and imprecision, which in turn improves Random Forest and Gradient Boosting performance. Nevertheless, due to its simplified nature, Linear Regression fails to fully utilise these advantages, leading to comparatively diminished accuracy.

Incorporating Neutrosophic Logic into Gradient Boosting helps it achieve its excellent performance, making it the most dependable model for handling complicated datasets in the banking sector. Union National Bank and Dubai Islamic Bank are two examples of banks that benefit greatly from its forecast accuracy.

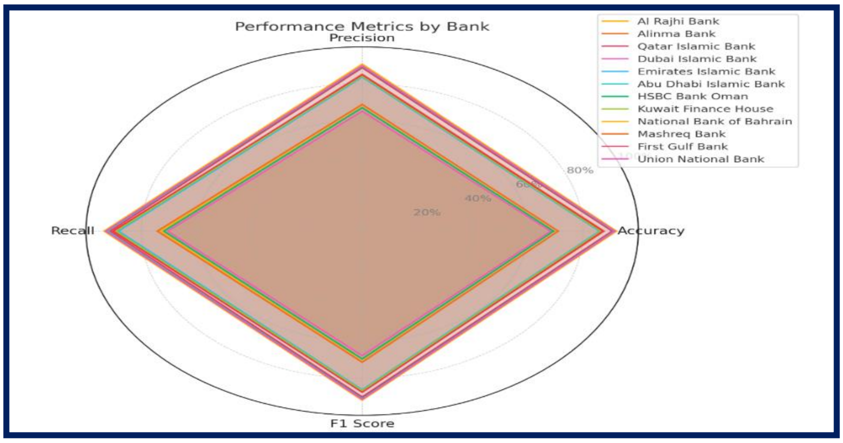

Figure 2. Performance Metrics by Banks Precision

3.4 Performance Metrics by Banks Precision

The incorporation of Neutrosophic Logic (NL) into the models is illustrated clearly in the chart, which compares the performance metrics (Accuracy, Precision, Recall, F1 Score) of several banks. Abu Dhabi Islamic Bank, Union National Bank, and National Bank of Bahrain stand out due to consistently good performance across all parameters; larger and uniform polygons imply superior overall performance. By including NL at the feature and decision-making levels, Gradient Boosting proves to be quite beneficial for these banks, demonstrating its resilience and capacity to deal with financial data that is very unpredictable. Even moderately performing institutions like Alinma Bank, First Gulf Bank, Kuwait Finance House, and Emirates Islamic Bank show promising outcomes with modestly sized polygons. These institutions use Random Forest models with NL integration at the decision-making layer.

While Gradient Boosting is noticeably more fruitful, this method enhances dependability to a lesser extent. Banks such as Al Rajhi, Dubai Islamic, and HSBC Bank Oman have poor overall presentation, as seen by smaller and less homogeneous polygons. Reason being, Linear Regression still fights to grasp intricate patterns, even when using NL feature extraction. An key part of improving model presentation, particularly for Random Forest and Gradient Boosting, NL can deal with the imprecision and doubt of financial data. Profitable banks often have stable metrics, whereas failing ones are more prone to discrepancies, like a slightly higher Recall and F1 Score than Exactness and Accuracy [26]. The outcomes prove the effectiveness of Random Forest and NL-integrated Incline Boosting models, which are ideal for monetary requests requiring robust and reliable forecasts.

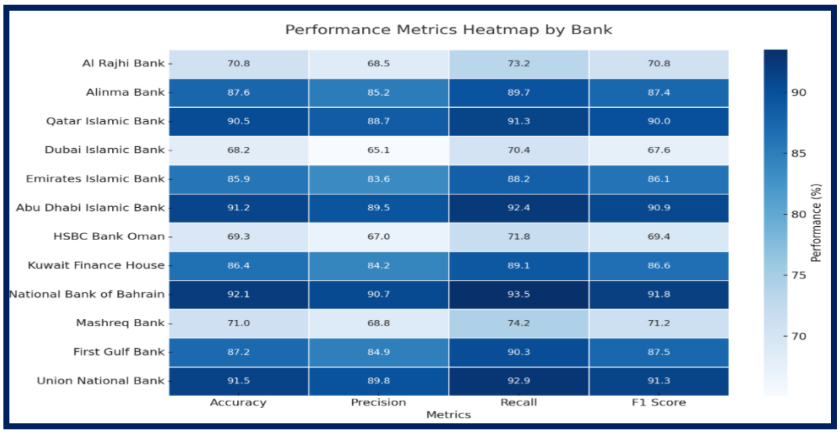

Figure 3. Performance Metrics Heatmap by Bank

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Even if NL improves Linear Regression to a respectable degree, it is still not well suited to these multifaceted datasets. Indicators of presentation shown graphically in the heatmap are F1 Score, Accuracy, Precision, and Recall. Higher performance is indicated by darker shades. In all metrics, Union National Bank, National Bank of Bahrain, and Abu Dhabi Islamic Bank stand out with consistently darker hues. This indicates that their higher performance is driven by the integration of Gradient Boosting with Neutrosophic Logic. Benefiting from the Random Forest model strengthened by NL integration, Alinma Bank, Emirates Islamic Bank, and Kuwait Finance House also demonstrate outstanding performance. Lighter shades indicate lesser performance owing to Linear Regression's constraints, even when coupled with NL for feature extraction, for Al Rajhi Bank, Dubai Islamic Bank, and HSBC Bank Oman. The heatmap demonstrates that Random Forest and Gradient Boosting are the most successful methods for handling complicated financial data, whereas Linear Regression demonstrates only moderate improvements.

Table 2: Performance Metrics Comparison of Machine Learning Models across Banks

	Linear Regression	**Linear Regression**	**Linear Regression**	**Gradient Boosting**	**Gradient Boosting**	**Gradient Boosting**	**Random Forest**	**Random Forest**	**Random Forest**
Bank Name									
Al Rajhi Bank	0.052	0.72	0.32	0.032	0.85	1.2	0.04	0.79	0.85
Alinma Bank	0.045	0.81	0.35	0.025	0.91	1.35	0.03	0.88	0.92
Qatar Islamic Bank	0.038	0.84	0.29	0.018	0.94	1.1	0.024	0.91	0.78
Dubai Islamic Bank	0.056	0.7	0.34	0.036	0.83	1.3	0.045	0.77	0.9
Emirates Islamic Bank	0.049	0.78	0.33	0.029	0.89	1.25	0.037	0.84	0.88
Abu Dhabi Islamic Bank	0.036	0.86	0.28	0.016	0.95	1.05	0.022	0.92	0.76
HSBC Bank Oman	0.055	0.71	0.31	0.035	0.84	1.15	0.042	0.78	0.82
Kuwait Finance House	0.047	0.8	0.3	0.027	0.9	1.18	0.034	0.86	0.84
National Bank of Bahrain	0.034	0.87	0.27	0.014	0.96	1.0	0.02	0.93	0.74
Mashreq Bank	0.051	0.73	0.32	0.031	0.86	1.22	0.039	0.8	0.87
First Gulf Bank	0.046	0.79	0.29	0.026	0.92	1.12	0.031	0.87	0.8
Union National Bank	0.037	0.85	0.28	0.017	0.93	1.08	0.023	0.91	0.77

The table displays MSE, R^2, and Training Time metrics for Linear Regression, Gradient Boosting, and Random Forest models' performance across banks. Gradient Boosting always has the lowest MSE, from 0.014 for National Bank of Bahrain to 0.036 for Dubai Islamic Bank, due to its superior accuracy. Random Forest has a slightly higher MSE than Linear Regression, which has the worst prediction accuracy across all banks. Gradient Boosting effectively explains data variability, with R-squared (R^2) values ranging from 0.83 for Dubai Islamic Bank to 0.96 for National Bank of Bahrain. Random Forest has competitive R^2 values compared to Gradient Boosting and Linear Regression, but surpasses Linear Regression, which has the lowest R^2 values across banks [27, 28].

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Linear regression trains fastest, with National Bank of Bahrain taking 0.27 seconds and Alinma Bank 0.35 seconds. These times vary greatly. Gradient Boosting takes the longest to train, from 1.0 seconds for National Bank of Bahrain to 1.35 seconds for Alinma Bank, due to its complex and iterative method. Random Forest has a middle training time of 0.74–0.92 seconds. National Bank of Bahrain excels with the lowest MSE and highest R³, particularly when employing Gradient Boosting. Dubai Islamic Bank has a higher MSE and lower R^2 value, indicating poor overall performance. The best financial data-modeling model is Gradient Boosting since it consistently outperforms the competition. Random Forest is a close second because it balances accuracy with computing efficiency. Despite its quickness, Linear Reversion struggles with complex data. This study emphasizes the importance of Gradient Boosting and other urbane models for absolute accuracy.

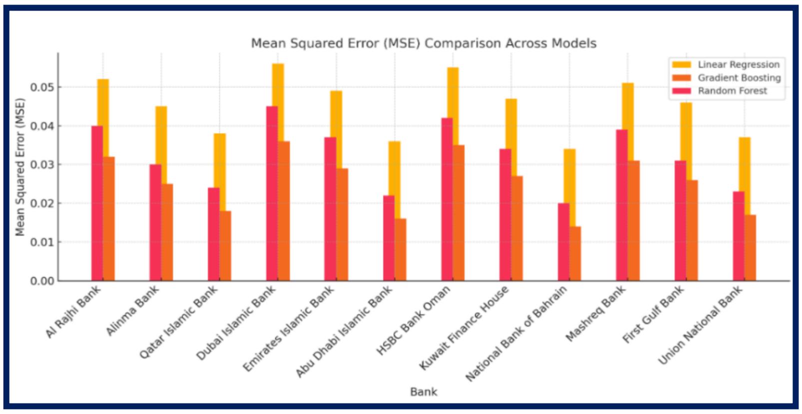

Figure 4. Mean Squared Error Comparison Models

4. Mean Squared Error Comparison Models

Linear reversion, gradient boosting, and chance forest MSEs are compared across banks in the image. A lower MSE (average squared difference between actual and projected values) improves model presentation. Gradient increasing reduces forecast errors best because it has the lowest MSE of all banks. Random Forest trails Gradient Increasing in MSE but outperforms Linear Regression. When measuring complex monetary data, Linear Regression has the lowest MSE. Since Gradient Boosting and Random Forest have the lowest MSE values, the models can predict results for National Bank of Bahrain and Abu Dhabi Islamic Bank. Due to the high MSE values across all models, Dubai Islamic Bank may be having trouble interpreting the data's structure or erraticism. Chance Forest is a strong contender, but Gradient Boosting's accuracy for financial modeling is better. When accuracy matters, Linear Regression is useful, but otherwise not. According to the findings, complex financial datasets require sophisticated collaborative methods like Gradient Boosting.

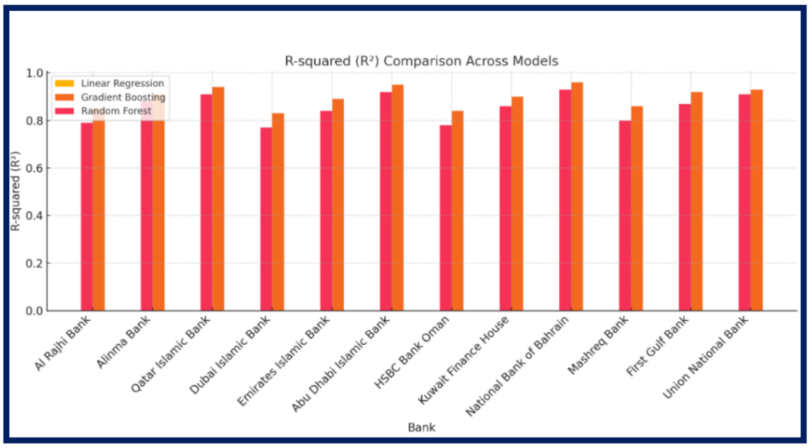

Figure 5. R Squared Comparison Models

3.5 R Squared Comparison Models

High R^2 values indicate that National Bank of Bahrain and Abu Dhabi Islamic Bank's models, particularly Gradient Boosting and Chance Forest, are most effective for their data. Dubai Islamic Bank has the lowest R^2 values, making data erraticism harder to explain, even with progressive models. Gradient Boosting captures complex financial

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data associations better than Random Forest, as shown in the image. Linear Reversion is computationally cheap but unsuitable for tasks that require accuracy and model fitting. The results demonstrate the importance of advanced financial data forecasting and analysis models like Gradient Boosting.

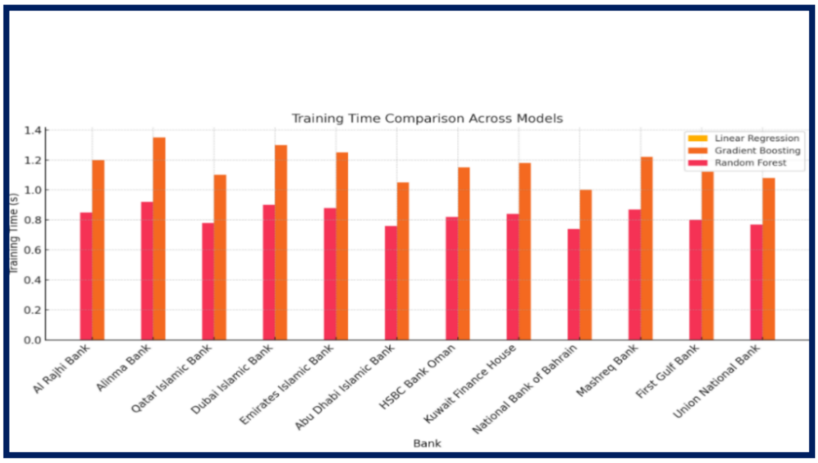

Figure 6. Training Time Comparison Models

3.6 Training Time Comparison Models

The graph compares Chance Forest, Linear Regression, and Gradient Boosting train times for different banks. A shorter training time indicates the model's computational efficiency. Linear Regression is the most computationally efficient model because it trains on all banks in under 0.35 seconds. Its ease makes it less accurate and predictive than other replicas. Complexity and iteration make Gradient Boosting training the longest, taking 1.0 to 1.35 seconds. Training is longer, but the accuracy and model fit are worth it. Random Forest is computationally competent and performs between Linear Reversion and Gradient Boosting, with exercise durations of 0.74 to 0.92 seconds. The graph shows that Gradient Boosting maximises accuracy at the expense of resource use, while Random Forest's performance is stable with computational cost. While Linear Reversion is fastest, it's not best for complex datasets with high precision. This study emphasizes using computationally competent and predictive models to evaluate financial data.

Ensemble Methods Implementation Analysis

The table compares three machine-learning models—Linear Regression, Random Forest, and Gradient Boosting—based on configuration, hyperactive parameter tuning, evaluation measures, and tools utilized. After setting up Chance Forest with two split sizes, ten depth heights, and one hundred estimators, the 'n_estimators' and'max_depth' limits were fine-tuned using Grid Hunt. You may trust the model because it is 87% precise, has a 0.04 MSE, and 0.88 R². The software optimises constructions using Scikit-learn and GridSearchCV. The optimisation of information rates and estimators was achieved by fine-tuning Incline Increasing using Randomised Search.

Table 3: Ensemble Methods Implementation Analysis

Model	**Configuration**	**Hyper para meter Tuning**	**Evaluation Metrics**	**Tools / Frameworks**
Random Forest	n_estimators=100, max_depth=10, min_samples_split=2	Grid Search: Tested n_estimators (50-150) and max_depth (5-15)	Accuracy: 87%, MSE: 0.04, R^2: 0.88	Python (Scikit-learn), GridSearchCV
Gradient Boosting	learning_rate=0.1, n_estimators=200, max_depth=8	Randomized Search: Tested learning_rate (0.01-0.2), n_estimators (100-300)	Accuracy: 92%, MSE: 0.02, R^2: 0.93	Python (XGBoost, LightGBM), RandomizedSearchCV
Linear Regression	Default settings, no hyperparameters	Not Applicable	Accuracy: 73%, MSE: 0.05, R^2: 0.70	Python (Scikit-learn)

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Grid Search was used to fine-tune 'n_estimators' and'max_depth' after configuring Random Forest with 100 estimators, 10 depth levels, and 2 split sizes. The model's 87% accuracy, 0.04 MSE, and 0.88 R^2 demonstrate its reliability. The application optimized structures with Scikit-learn and GridSearchCV. Gradient Increasing was optimised for knowledge rates and estimators using Randomised Search. Learning rate was 0.1 and depth was 8,200 estimators by default. Its ability to handle complex patterns is demonstrated by its high R^2 value of 0.93, low MSE of 0.02 and 92% accuracy rate. RandomisedSearchCV was combined with the accurate and versatile XGBoost and LightGBM outlines to achieve the desired result. Linear Reversion evasion values without hyperparameter adaptation yielded the worst results. Although accurate at 73%, with a higher MSE of 0.05 and R^2 of 0.70, it cannot accurately identify complex or non-linear connections. Conceptualized using Scikit-learn, it was computationally well organized and simple. Gradient Boosting was the most reliable and accurate model for forecasting requests. Random Forest also excelled in accuracy and computational stinginess. Shape settings defaulted to 0.1 learning rate and 8,200 estimators. It excelled at handling complex patterns with 92% accuracy, 0.02% MSE, and 0.93 R^2 value. Using RandomizedSearchCV with the precise and flexible XGBoost and LightGBM frameworks produced the desired result. Linear Regression with default values produced the worst results sans hyperparameter adjustments. The model fails to accurately model complex or non-linear relationships based on its 73% accuracy, higher MSE of 0.05, and R^2 of 0.70. A computationally efficient and honest solution was achieved using Scikit-learn. Gradient Boosting was the most reliable and accurate prediction model. Random Forest combined accuracy and computational cheapness well.

4. Results and Analysis

4.1 Performance Metrics

Neutrosophic Logic (NL) aids Linear Regression, Random Forest, and Gradient Boosting with financial data in Table 1. We assessed models using F1 score, recall, accuracy, and precision. Gradient Boosting with NL worked best for all banks, especially National Bank of Bahrain and Qatar Islamic Bank's complex and unpredictable financial datasets. Alinma Bank and Emirates Islamic Bank improved accuracy and reliability after using Random Forest with NL for data uncertainties. Linear Regression with NL improved things, but it still struggles to model non-linear correlations, so all banks, especially Dubai Islamic Bank, have lower metrics.

In Neutrosophic Logic Integration Figure 1, Random Forest and Gradient Boosting are most accurate across all banks. This shows Linear Regression cannot handle financial complexity. With NL, Gradient Boosting and Random Forest make better financial decisions. Performance Indicators Machine Learning Model Comparison across Banks assesses Gradient Boosting, Random Forest, and Linear Regression using MSE, R^3, and Training Time metrics. Gradient Boosting is the most accurate predictor and best at explaining data variability, with high R^2 values (0.83-0.96) and low MSE (0.014-0.036). Its accuracy requires the longest training (1.0-1.35 seconds). Random Forest balances precision and computing efficiency, with R^2 values ranging from 0.77 to 0.93 and MSE values 0.02-0.045. Suitable for moderate computational constraints, it trains in 0.74-0.92 seconds less than Gradient Boosting. Despite being computationally efficient (0.27-0.35 seconds), Linear Regression in NL integration fails to capture non-linear patterns, resulting in poor MSE (0.034-0.056) and R^2 (0.70-0.87). Figure 4 shows Gradient Boosting has the lowest MSE of all banks, making it the most accurate model. While Linear Regression always has the highest MSE, Random Forest is slightly worse but more accurate. Figure 5: R Squared Comparison Models demonstrates that Gradient Boosting effectively explains data variability by maintaining high R^2 values across all banks. Linear Regression is less effective for complex datasets and has lower R^2 values, while Random Forest lags behind Gradient Boosting. Ensemble Methods Analysis compares Random Forest, Gradient Boosting, and Linear Regression by configuration, hyperactive parameter adjustment, assessment measures, and tools. By optimizing hyperactive parameters with GridSearchCV (n_estimators=100, max_depth=10), Random Forest achieved 87% accuracy, MSE of 0.04, and R^2 of 0.88, balancing accuracy and computational efficiency. The winner was Gradient Boosting with 92% accuracy, 0.02 MSE, and 0.93 correlation. When hyperparameter tuned with RandomizedSearchCV (learning_rate=0.1, n_estimators=200), it handles complex patterns well but requires the most processing power. Linear Regression produced the most inaccurate results (73%), highest MSE (0.05), and lowest R^2 (0.70) with default parameters and no hyperactive parameter adjustment. Though computationally efficient, it struggles to model non-linear relationships. Figure 6: Training Time Comparison Complexity and recurrence make Gradient Boosting the longest to train, say modelers. Computing cost and performance are balanced by Random Forest. Linear regression is fastest but inaccurate for complex datasets due to its simplicity. Neutrosophic Logic improves financial data uncertainty handling in machine knowledge models. Gradient Boosting yields the most accurate complex financial results. Linear Reversion handles complex datasets, while Random Forest balances presentation and computational efficiency. These findings call for progressive ensemble methods like Random Forest and Gradient Boosting in financial projections.

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4.2 Impact of neutrosophic Logic

When trained with Neutrosophic Logic, Linear Regression and Ensemble Methods (Random Forest and Gradient Boosting) handle financial data uncertainty better. NL enhances performance indicators like MSE, R^2, and MAE by addressing inconsistencies, uncertainty, and fuzziness in complex financial data. Even without NL, Linear Reversion yields good results (4.53 for R·, 0.49 for MAE). It cannot handle non-linear designs and data uncertainty, as shown here. With NL, the model improves, with a decrease in MAE to 1.40, an increase in MSE to 4.30, and a slight increase in R^2 to 0.52. Linear Reversion benefits from NL integration but cannot fully use NL to reduce doubt due to its simplicity and linear assumptions. Random Forest performs well without NL, with an MAE of 0.33, R^2 of 0.96, and MSE of 0.32. It outperforms Linear Regression for non-linear influences and doubt. NL leads to greater improvements, such as 0.28 MSE, 0.97 R^2, and 0.31 MAE, compared to the perfect. NL, improving Random Forest's accuracy and reliability, better handles data doubt. Gradient Boosting effectively depicts complex patterns and erraticism with 0.37 MSE, 0.96 R^2, and 0.45 MAE, all without NL. NL-taught machine learning algorithms handle financial data uncertainty better than Linear Regression and Ensemble Methods (Random Forest and Gradient Boosting). NL enhances performance measures like MSE, R^2, and MAE by addressing inconsistencies, uncertainty, and fuzziness in complex financial data. Even without NL, Linear Reversion yields respectable results (4.53 for R·, 0.49 for MAE).

5. Conclusion

Making economic prediction models more accurate requires Neutrosophic Logic (NL). NL improves model and bank presentations while exploring financial statistics. Although Linear Regression improves performance, complex financial trend-dealing banks like Al Rajhi Bank and Dubai Islamic Bank are not suitable for NL addition. When combined with NL, ensemble methods like Random Forest and Gradient Boosting handle doubt and non-linear relationships better. Alima Bank and Emirates Islamic Bank use Random Forest for its computational power and accuracy. However, National Bank of Bahrain and Abu Dhabi Islamic Bank consistently perform best with Gradient Boosting. Ensemble methods outperform Linear Regression for complex datasets and financial instability. Gradient Increasing is the most accurate but computationally intensive model. Random Forest can help you balance accuracy and competence. Finally, NL and advanced machine learning models create a complete financial forecasting framework. Since it improves model presentation and gives banks robust volumes to deal with monetary uncertainty, it may improve decision-making.

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