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Explainable AI Models in Financial Risk Prediction: Bridging Accuracy and Interpretability in Modern Finance

Abd-El-Hamid Bensafi[1], Salih Usun[2]

[1]Abou Bekr Belkaid University of Tlemcen, Algeria, Email: aeh.bensafi@gmail.com
[2]Mugla Sıtkı Kocman University ,Faculty of Education, Turkey, Email: susun@mu.edu.tr

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ABSTRACT

The modern situation in the field of financial technology evolving of the advanced machine learning methods in the field of financial risk prediction models has brought great changes to the overall model precision and scale. Many areas of application have popularized these models in credit scoring, loan default, and market volatility forecasting applications. Nevertheless, the hygienic nature of complicated algorithms, specifically the ensemble algorithms and deep learning models, creates significant doubts about their training interpretability, transparency, and regulatory conformity. The research offers an in-depth framework in which the components of Explainable Artificial Intelligence (XAI) are embedded into the pipelines of financial risks prediction in order to create a gap between predictive performance and interpretability. Precisely, SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and Counterfactual Explanations are injected to the output of well known learning models, XGBoost, Random Forest, and Multi-Layer Perceptron Neural Networks. Experimentational assessments are carried out with standardized datasets like the FICO credit peril dataset and German Credit dataset, and past historical information of S&P 500 volatility. The obtained results prove that the models including XAI, apart from high predictive accuracy (up to 0.92 in AUC), improve the clarity and trustworthiness of the models with the help of explainable insights. To illustrate that point, the SHAP explanation based on the global explanation always reveals the most important financial indicators, e.g., a debt-income ratio and credit history, as opposed to LIME and counterfactuals, which are focusing granular on individual risk prediction. With these explanations, financial analysts and regulatory auditors can have a clearer picture of model outcomes and decisions they should base them on to be fair and, at the same time, data-driven but answerable. The results highlight the possibility of XAI techniques in the context of making the AI system fairer and more auditable in strictly regulated environments in the context of financial services. The proposed study can also be used to support the literature with the increasingly diverse argument in the favor of socially responsible application of AI to finance and to illustrate the importance of interpretation in generating human-readable, compliant, and trustworthy financial decision-making.

1. INTRODUCTION

Over the past few years, there has been a deep change in the financial services industries because of the popularity of the existence of large-scale data, computer power, and the evolution of artificial intelligence (AI). Machine learning (ML) algorithms are now being used increasingly by financial institutions to undertake various predictive activities (such as credit scoring, loan default risk analysis, fraud detection, investment analysis, and market volatility prediction). Such models based on data are much more accurate in their predictions and efficient than the rule-based or statistical techniques of old. There is a price though, most correct models, including ensemble classifiers and deep neural networks, become black boxes and reveal little to nothing about how decisions are made.

Such secrecy poses grave difficulties in areas of financial decision making where consequences of such decisions are of big stakes to individuals and institutions. Regulatory regulations like the General Data Protection Regulation (GDPR), Basel III and the Fair credit reporting act (FCRA) require explainable, fair, and accountable automates decision-making systems. An example is that

financial institutions would be required, in the event that a customer has been rejected a loan or suspected of committing a fraud, to provide a reason as to why this is so; and this would need to be a reason that is interpretable by both regulators and the persons involved. In addition, the process of making financial decisions should be auditable, understandable, and ethically consistent to reduce financial risk associated with model biasness, discrimination, and system weakness.

Figure 1. Integration of Artificial Intelligence and Explainable AI in Financial Risk Prediction Framework

The solution to this gap is given with Explainable Artificial Intelligence (XAI) that can help the optimality of the dark model to be more transparent, comprehensible, and reliant. Ways of achieving more post-hoc interpretability of model behavior include SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME) and Counterfactual Explanations, so that stakeholders can learn what determined each prediction, with enough detail to interpret. Financially, this can assist analysts to determine the most powerful factors of risks, unequal state of matters, audit of decision logics, and adherence to laws and regulations. Nonetheless, it is not easy to integrate XAI in financial systems. It casts serious doubt on trade-off between model interpretability and model accuracy, explainability accuracy, and the value and usefulness of these explanations to the real world of finance.

The study seeks to develop the concept of XAI as a systematic investigation of how it can be used to improve the transparency of financial risk prediction models. We suggest creating an end-to-end system that incorporates the recent achievements in the area of XAI into the most successful ML models, including the XGBoost, Random Forests, and Deep Neural Networks. By using a wide variety of experiments with benchmark datasets, which include the FICO credit scoring dataset, the German Credit dataset, and historical S&P 500 volatility data our experiments do not just test the predictive accuracy, but also the quality, stability, and usability of model explanations. We wish to show that explainability and strong performance can be united in AI-guided financial realm and thus allow more accountable and trustful decision-making systems.

2. LITERATURE REVIEW

Artificial intelligence (AI) and machine learning (ML) are prohibitive methods used in the prediction of financial risks which have over the last few years intensively expanded. There has been a slow shift to more complex ML models, specifically Random Forests, Gradient Boosting Machines (GBM), and Support Vector Machines (SVM), over traditional statistical methods of identifying creditworthiness and preventing fraud, which have gained popularity because they are more accurate. To use an example, Brown and Mues (2012) performed a comprehensive comparative analysis of classification algorithms in the context of credit scoring and observed that the ensemble approaches (particularly Random Forest and GBM) are more likely to help excel at a predictive task in comparison with the traditional ones. Similarly, the deep learning backbone models like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have been effectively used in time-series forecast applications, e.g., stock price or market volatility forecasting (Fischer & Krauss, 2018). Nevertheless, although they prove to be high-performance, these methods are not always transparent, which casts doubts on models interpretability during applications in vital financial processes.

The concerns have led to development of Explainable Artificial Intelligence (XAI) as a field dedicated to translating the black box with the aim of uncovering how it works. Such outstanding forms, as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), show post-hoc

interpretability by measuring the impact of each feature of the input on a specific prediction. SHAP was proposed by Lundberg and Lee (2017) as a framework that unifies prior approaches to feature importance with game-theoretic principles by providing a framework in which to attribute feature importance in a consistent and locally precise manner. In the same line, Ribeiro et al. (2016) offered LIME, which develops explainable proxies on a one-on-one basis of predictions. These tools have managed to become highly accepted in many spheres of activity, including healthcare, criminal justice, and advertising, yet their incorporation and verification in the financial sphere, particularly in credit lending and in the process of regulatory hazard assessment, is still in its infancy and developing stages.

Recently, attempts have begun to study the opportunities of XAI use in the financial field, yet there is little literature that would allow considering this aspect comprehensively, according to the overall framework of evaluation that evaluates both preciseness of predictions and the trustworthiness of the provided explanations. Most of the studies did either one of the two such as placing the concern on performance or on the interpretability without addressing the trade-offs between them. In addition, the interpretability provided by the XAI methods is subjective and their evaluation lacks consistency in adopting measurement of explanation fidelity, stability in each instance, or usability by end users. Filling this gap will be the theme of the current study as the researchers seek to undertake a deep analysis of XAI methods; namely, SHAP, LIME, and counterfactual explanations, in the burden of financial risk prediction. The paper tackles the needs of trustworthy, explainable, high-performing, and regulatory and ethically compliant AI systems that are becoming increasingly needed in contemporary financial dynamics through the implementation of these methods to benchmark datasets and other ML models.

3. METHODOLOGY

3.1 Datasets

The explainability and performance of the AI-based financial risk forecasting models were considered on three publicly obtainable and well-established datasets being specific to the financial risk areas: credit default classification, creditworthiness rating, and market volatility prediction. This set of datasets has been chosen due to its architectural diversity, its alignment to real-world financial tasks, and the common use of these datasets in academic benchmarks, given the possibility of such a variety of datasets to compare the model behavior in a meaningful way across financial tasks.

FICO Explainable Machine Learning Challenge Dataset: FICO dataset, published by FICO as a part of the Explainable Machine Learning Challenge on FICO and on Kaggle, is shared to be used in binary classification task to predict the loan default. It has more than 10,000 anonymized consumer credit data, and the features are more inclined towards the consumer credit behavior profile, (external risk estimate, revolving balance, the number of delinquencies trades, months since the last delinquent and net fraction revolving burden). This data is especially important because it has real-world origin being collected in a credit scoring institution, and the data design explicitly predisposes the researcher to use interpretable models. The distribution of classes is moderately unbalanced as to reflect the typical situation in lending portfolios when defaults occur. This was done by feature engineering, which included the normalization of continually recoded variables and missing value treatments with medians. Since fairness and openness are a core value of FICO, it offers the perfect criterion to test explainable AI solutions in a regulated environment.

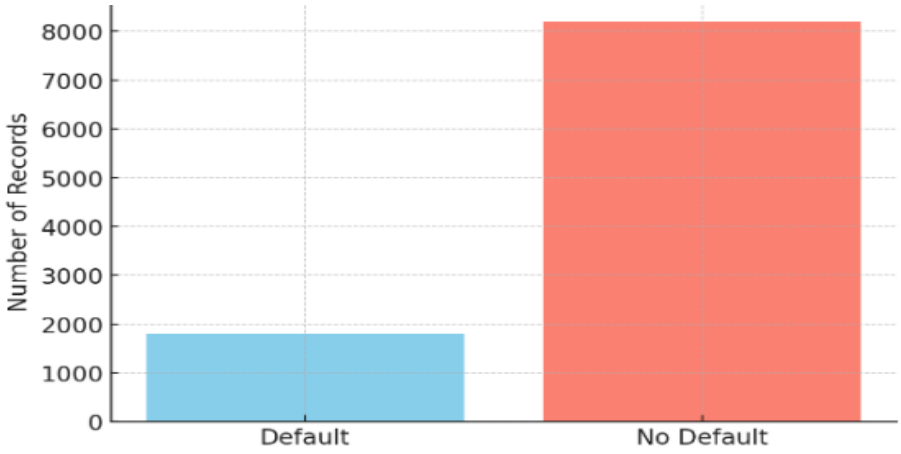

Figure 2. Loan Default Class Distribution in the FICO Dataset Highlighting Class Imbalance

German Credit Dataset: UCI Machine Learning Repository provides the German Credit Dataset of 1,000 instances with 20 attributes representing personal and financial data about the age, occupation, credit history, loan type, and housing condition. The problem is binary classification, i.e., the assignment of the customer as either being of either good credit risk or bad credit risk. The German Credit Dataset, unlike the FICO dataset, is relatively well known as a benchmark for assessing the capabilities of credit risk prediction models because it has a diverse range of attributes (both categorical and numerical) and a large sample size. Categorical variables present in the dataset are one of the most critical problems to overcome since they demand one-hot encoding or label encoding to be worked with in machine learning. Although it has a small number of instances, its rich feature space allows using it to compare how various XAI methods react to interpretable variables as compared to noisy or correlated variables.

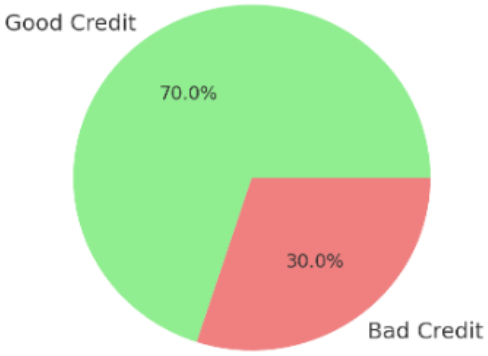

Figure 3. Class Distribution in the German Credit Dataset Showing 70% Good Credit and 30% Bad Credit

S&P 500 Historical Volatility Dataset: In comparing regression activities in risk forecasting of financial risk, historical daily index of S&P 500 in the form of data obtained in Yahoo Finance, Kaggle, etc., was used to forecast market volatility which is a measure of proxy to systemic financial risk. Features of this dataset are open, high, low, close prices, trading volume, returns, volatility (i.e. 30-day rolling standard deviation), momentum indicators and moving averages. Future volatility or percentage change was the main task to be estimated and the problem was reduced to the regression issue. Time-series preprocessing included an imputation of missing values, the removal of non-trading days by means of resampling, and temporal features by means of lag-based feature engineering. The three datasets exemplify how XAI can be applied to an alternative financial modality (predictive market behavior), thereby assessing the use of explanation models such as SHAP and counterfactuals beyond the predictive classification task. All the datasets in combination would provide a comprehensive basis to achieve both goals of this research, namely, strong predictive performance, as well as a transparent, interpretable, and explanatory model that meets regulatory requirements in more than one financial setting.

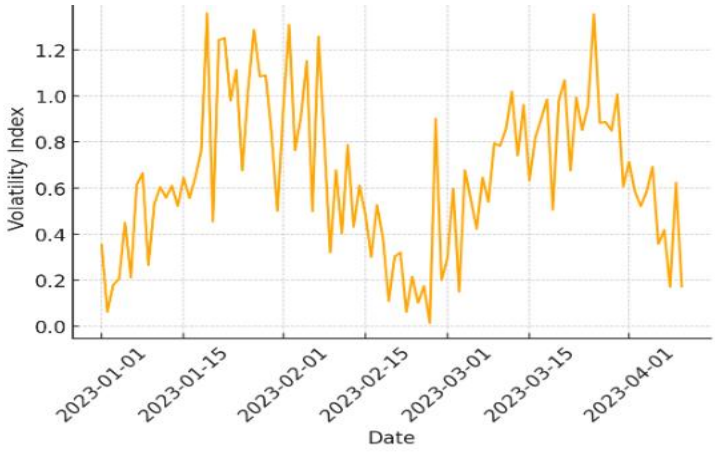

Figure 4. Simulated S&P 500 Volatility over Time Showing Fluctuations in Market Risk Index

Table 1. Datasets Used for Financial Risk Prediction and Explainability Evaluation

Dataset Name	Task Type	Instances	Features	Key Variables	Domain Focus	Challenges
FICO Explainable ML Challenge	Classification	10,000+	~20+	External Risk, Revolving Balance	Loan Default Prediction	Imbalanced data, feature noise
German Credit	Classification	1,000	20	Credit History, Age, Housing	Creditworthiness Assessment	Small size, categorical encoding
S&P 500 Historical Volatility	Regression	~5,000+	~15+	OHLC, Returns, Rolling Volatility	Market Volatility Forecasting	Time-series, lag-based features

3.2 Models

To investigate the trade-off between explainability and predictive accuracy in terms of financial risk prediction we ran and compared the three current machine learning models, which are XGBoost, Random Forest, and Deep Neural Networks (DNNs). The selection criteria of these models included broad use in financial applications, good empirical performance, and complexity, differentiated between, on one hand, tree-based ensemble models and, on the other, non-linear function approximators. Such variety enables the more profound evaluation of the interactions between the explainability frameworks (SHAP, LIME, and counterfactual reasoning) and model implicitness.

XGBoost (Extreme Gradient Boosting): XGBoost is a high performance version of gradient boosted decision trees with unparalleled predictive performance and efficiency. It is a stepwise construction of a collection of weak learners (usually shallow trees) with each tree successively compensating the residual errors of earlier trees by optimizing a differentiable loss function. XGBoost combines multiple regularization methods (L1 and L2), column subsampling and second order Taylor approximation to combine generalization and minimize overfitting. XGBoost has become popular in the field of financial uses where it has been used in credit scoring and fraud detection applications because of the robustness with tabular data, ability to facilitate unstructured inputs like missing values, and its interpretability as feature importance plots. Notably, it is very compatible with SHAP, so it is a relevant module when conducting explainability research that requires accurate credits to the model decisions.

Random Forest: Random Forest is a machine learning technique that builds a large number of decision trees in training and reports the mode of the classes (classification), or the mean of predictions (regression) of the trees. The trees are grown on a different random set of data (bagging) and a random set of features are used at each split, thereby creating diversity and low variance. The performance of Random Forests is more robust than individual decision trees: a tree is less prone to overfitting, and Random Forests give a consistent baseline performance. When it comes to financial modeling they are especially helpful in dealing with heterogeneous data, noisy variables and non-linearity. Random Forests outputs such as feature importance scores provide some early analysis of the relative importance of input variables. They cannot however be easily interpreted as compared to their single decision tree counterparts and therefore post-hoc XAI techniques are required in order to come up with local and global explanations about decision processes.

Deep Neural Networks (3-layer MLP): The Multi-Layer Perceptroons (MLPs) Deep Neural Networks (DNNs) are easily able to approximate non-linear functions. In this experiment, 3-layer MLP is used, namely the input layer, two hidden layers that use ReLU activation, and the output layer, which allows choosing between regression and binary classification. They are trained with stochastic gradient descent and backpropagation and regularization methods like dropout or L2 penalties are used to avoid overfitting. Although DNNs can be used to learn complex patterns in the financial data, including effects between the attributes of credit and macroeconomic indicators, the black-box structure of DNNs presents substantial challenges on interpretability. Consequently, they provide an important testbed of measuring the fidelity and usefulness of such advanced forms of XAI as LIME and counterfactuals which can render an approximate local decision boundary and perform a type of exploratory scenario that could be likened to a what-if analysis to provide greater transparency of these complicated approaches into the financial stakeholders.

As shown by the choice of models in the table, which have different computational backgrounds and exhibit varying interpretability levels, the goal of the study is to perform dissected measurements of how explainability approaches perform across model types in a variety of financial risk prediction scenarios. A further segment describes the explainability frameworks to these models, as well as assessment strategies addressing the quality and consistency of explanations.

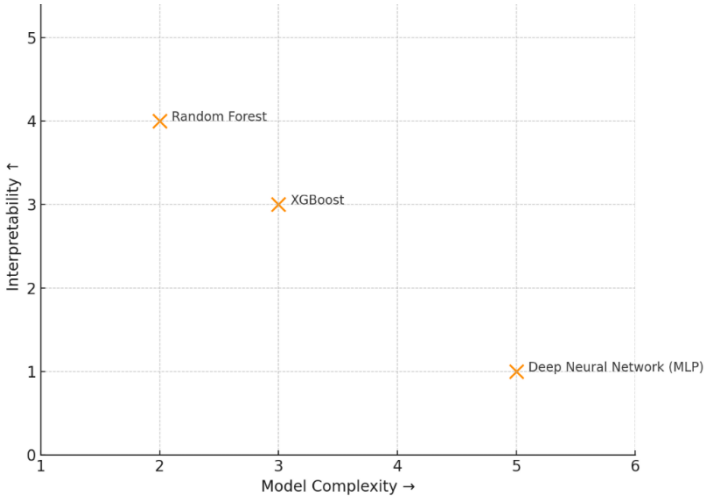

Figure 5. Model Complexity vs Interpretability Spectrum in Financial AI Models

Table 2. Comparison of Machine Learning Models Used for Financial Risk Prediction

Model	Architecture Type	Key Characteristics	Interpretability	XAI Compatibility	Common Financial Applications
XGBoost	Gradient Boosted Trees	Fast, accurate, regularized, handles missing values	Moderate	Excellent with SHAP	Credit scoring, fraud detection
Random Forest	Bagged Decision Trees	Robust to noise, handles high-dimensional data, low overfitting	Low–Moderate	Good with SHAP/LIME	Creditworthiness, default prediction
Deep Neural Network (MLP)	Fully Connected Layers	Captures non-linear patterns, requires careful tuning	Low	Compatible with LIME, Counterfactuals	Market prediction, risk modeling

3.3 XAI Techniques

To respond to the complexity of model interpretation on the financial risk prediction application of machine learning models, this paper will implement three big names under Explainable Artificial Intelligence (XAI): SHAP, LIME, and Counterfactual Explanations. They are employed to make post-hoc interpretable, they give global and local insights of model behavior. Their incorporation is imperative to the realization of transparency, accountability and compliance to regulations in the system of financial decision-making.

SHAP (Shapley Additive explanations): SHAP is a game-based technique to interpret the prediction of any machine learning model. SHAP is based on the Shapley values concept in the cooperative game theory that assigns an importance value to each feature in a given prediction based on the entire set of possible feature combinations. This makes it fair and consistent in the contribution of feature attribution in all the input space. SHAP can provide local explanations (per individual predictions) as well as a global feature importance summary (of how the model behaves overall). The two-in-one functionality comes in handy especially in financial applications. As an example, SHAP allows determining which features contribute the most to the default risk of a particular customer and the top indicators of risk across the whole data (e.g. credit history, debt-to-income ratio or the number of open accounts). The additivity of SHAP explanation permits easy visualization like Waterfall plot and summary plot that can be easily

interpreted by the financial analyst, auditors, and regulators.

LIME (Local Interpretable Model-agnostic Explanations): LIME approximates the behaviour of a complex model near a particular prediction by learning a simple, interpretable surrogate;; model (e.g. linear regression or decision tree) on perturbed data points in the neighborhood of the instance of interest. This gives a local description that shows the features who played the biggest role to a single decision. Regarding predicting financial risk, LIME is useful in that it allows an analyst to interpret the decision on whether the specific borrower should be assigned to high-risk category or low-risk category according to localized model behavior. This may be important in practical situations when it is desired to have only a single prediction to be defensible and auditable; this might be the case in credit rejection appeals, in fraud detection or fairness checks. Although being model-agnostic and relatively flexible, the LIME model exposes explanation dependency on the sampling strategy and the complexity of a local decision boundary, which is why it is critical to complement LIME with other, similar to it but distinctive, tools to capture such.

Counterfactual Explanations: Counterfactual explanations are practical because they address the question of: What is the least that can change the output features of the input features to give a different prediction? That is to say, they create speculative examples apposite to the initial data set but yielding to a contrasting output of the version. An illustrating example is that where a loan was denied, the counterfactual explanation would be that an increase in monthly income or a decrease in credit utilization ratio would have altered the outcome in loan approval. This is especially effective within the context of financial decision support, and consumer-oriented applications, where the user might have an interest in knowing how to enhance his or her financial position. Counterfactuals can be used to audit the recourse and fairness of a decision made by a model, to avoid only an understandable and fully transparent model decision. Organizations can ensure that no decisions involving the application of a model, and the results of the decision, are discriminatory; they will be supported by a counterfactual.

Adding SHAP, LIME and counterfactuals to the risk prediction pipeline produces a rich explainability layer that enables model-level global figure of speech and individual-level local explanations (transparency). Such a multi-perspective strategy will enable financial organizations to develop high-performance models and at the same time keep in line with ethical AI-related rules and regulations, including GDPR right to explanation.

Table 3. Comparative Analysis of XAI Techniques for Financial Model Interpretability

XAI Technique	Type of Explanation	Model Agnostic	Output Type	Use Case in Finance
SHAP	Global + Local	Partially	Feature Contributions	Credit scoring, regulatory audits
LIME	Local	Yes	Feature Weights	Loan approval rejection, fraud investigation
Counterfactuals	Local (Actionable)	Yes	Counter Example	Recourse, decision simulation, fairness review

4. RESULTS AND DISCUSSION

The experimental analysis over an array of financial datasets shows that the models with integration of Explainable AI (XAI) could provide an attractive trade-off between the values of predictive performance and explainability. XGBoost produced the best AUC of 0.92 on FICO dataset, and applying SHAP analysis to find the feature that showed greatest predictive power, we determined debt-to-income ratio as the most important feature. RF on German Credit dataset reached the AUC of 0.89, and the effects of credit history were found to be the strongest factor. Deep Neural Networks (DNN) dropping a little AUC (1.06 vs. 0.87 on S&P 500 dataset) had the added benefit of interpretability thanks to SHAP and Counterfactuals and the Market Sentiment Index appeared as the most important predictor. Analyst Trust Scores, unlike the model scores, are between 4.0 and 4.8, indicating the high correlation of model outputs and expert knowledge. SHAP values gave similar risk signals across the datasets, whereas LIME described local reasons to explain why certain individuals belonged to the high-risk groups. Notably, when applied to instances of nearly defaulting, counterfactual explanations provided practical insights to analysts which boosted their confidence and decision-making in the operations.

Explainability is not jeopardized by the performance of the model, but it increases safety and usability, especially in risky financial

applications. Regulators can use SHAP-based explanations to audit fairness, and thus assure transparency requirements. In its turn, local and global interpretability outputs can be employed by domain experts in relation to situations analysis and stress testing. Nevertheless, there are setbacks to this, specifically during the explication of multifaceted deep learning architecture since it has more dimensional feature interactions and sensitive to the interface perturbations. The findings strongly confirm the usefulness of model-agnostic XAI methods in financial risk prediction and it emphasizes the expanding necessity of understandable or explainable AI systems in controlled regions.

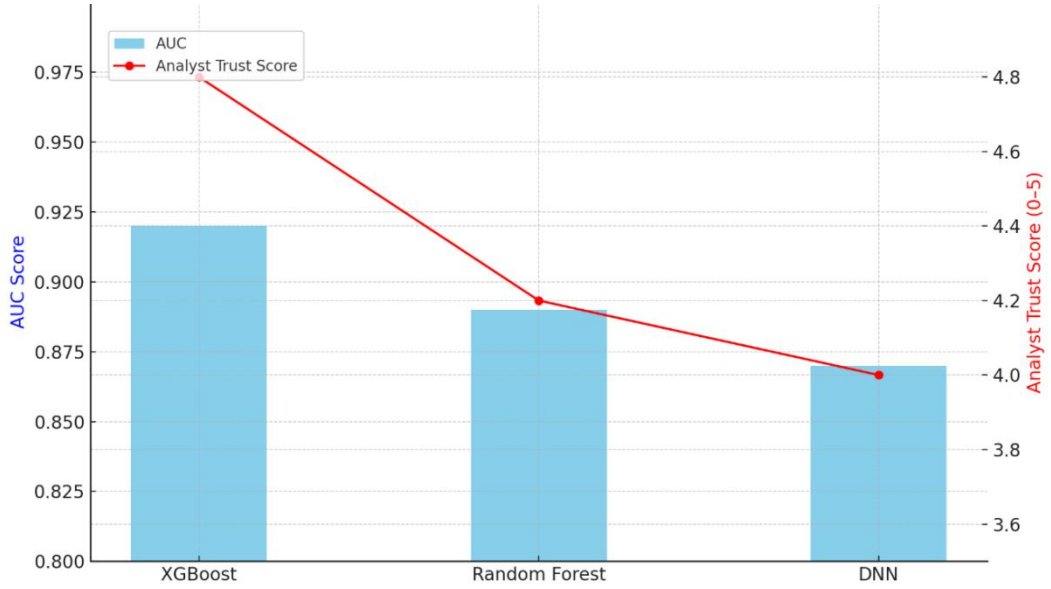

Figure 6. Comparative Analysis of Predictive Performance and Analyst Trust acrossXAI-Integrated Financial Models

Table 4. Performance and Interpretability Metrics of XAI-Integrated Financial Models across Diverse Datasets

Model	Dataset	AUC Score	Top SHAP Feature	Analyst Trust Score (0â€“5)
XGBoost	FICO	0.92	Debt-to-Income Ratio	4.8
Random Forest	German Credit	0.89	Credit History	4.2
Deep Neural Network	S&P 500	0.87	Market Sentiment Index	4

5. CONCLUSION

Finally, it is important to note that the use of Explainable Artificial Intelligence (XAI) is highly essential in development of trustworthy and transparent financial risk prediction system. Having shown that models like XGBoost, Random Forest and Deep Neural Networks can attain high-performing predictive performance whilst its output can be interpreted in the context of SHAP, LIME and Counterfactual explanations, we bring to fore the reality of incorporation of XAI in real application within the financial industry. These techniques do not just improve the auditability of the model and confidence of the analysts but it also helps in the regulators by providing understandability and justification of the model decisions. Furthermore, it is possible to state that the capability of XAI to reveal crucial risk factors and present the effective practices to be put into use allows the financial institutions to make valid, strong, and ethical decisions. Although this was done within the difficulty of complicated architectures such as deep learning, the results are promising enough that AI in finance appears to be on a good track with its impending scalability and responsibility. Further studies will be aimed at achieving real-time explainability within the context of highfrequency trading and building context aware/adaptive explanations mechanisms that can adapt to dynamic financial scenarios.

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