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# Fair Valuation for Financial Instruments using AI/ML

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**Abstract:** The research determines which Artificial Intelligence techniques such as Support Vector Regression (SVR), XGBoost and Artificial Neural Networks (ANN) provide optimal results for fixed-income financial instruments' fair value assessment throughout global markets. The paper examines how the methods function against traditional valuation principles such as DCF and Black-Scholes while showing their weaknesses when working with unclear or scarce data patterns. The research uses July 2024 fixed-income market data to deploy support vector regression (SVR), extreme gradient boosting (XGBoost), and artificial neural network (ANN) models for comparison. These models receive assessment based on their predictive power of instrument ask prices through evaluation of duration and convexity alongside coupon rate and issuer leverage, and yield metrics. The predictive model utilizing XGBoost delivered superior accuracy than SBVR by producing an RMSE of 0.0069 and $R^2$ of 0.9997. SBVR achieved results comparable to XGBoost, having an RMSE of 0.0113 and $R^2$ of 0.9990. The ANN model demonstrated poor performance against other models because it produced an RMSE of 0.519 and an $R^2$ of 0.662 during financial data predictions. XGBoost, utilized with SHAP (Shapley Additive exPlanations) values, generated explainable models that met the requirements of IFRS 13. The DCF model produces one fixed value of 100, while AI/ML models are adjusted to market conditions during valuation, which results in enhanced accuracy. The study findings demonstrate that XGBoost and SVR models effectively determine exact valuations in developed and emerging economies through SHAP techniques that fulfill the requirements of IFRS 13 reporting requirements. Researchers plan to develop ensemble models together with expanding their approach to the valuation of assets beyond fixed income instruments.

**Keywords**: *Artificial Intelligence, Machine Learning, Extreme Gradient Boosting, Support Vector Regression, Artificial Neural Network, Fair Valuation*

## Introduction

Fair valuation describes the method to determine the actual market worth of financial assets or liabilities through analysis of current market data and available market input information (Chadda and Vardia, 2020). The standards supported by International Financial Reporting Standards (IFRS) and Generally Accepted Accounting Principles (GAAP) maintain financial stability through this established valuation process (Prasad, 2024). Financial market stability depends on exact valuation because it supports investment choices as well as both financial institutions' proper operation and overall economic performance. Multivariable asset valuation depends heavily on traditional models including DCF, Black-Scholes and Monte Carlo simulations because of their extensive application in the field. Their fundamental assumptions fail to deliver satisfactory results in current financial market conditions particularly when volatility or thin trading occurs or when transactions span borders. DCF calculates asset values by analysing anticipated future cash flows, yet Black-Scholes functions as a standard to determine option and derivative prices through volatility and time variables (Moore, 2023). The flexibility of Monte Carlo simulations allows users to handle complex financial situations through random sampling methods which analyse uncertainty (Velikova et al., 2024). These fundamental forecasting methods remain important but struggle to handle the current financial environment because rising market complexities and variable market swings make their core principles less valid (Bao et al., 2024).

Actual market reactions are not revealed with the use of combination of historical data, along with the basic market outlooks within the traditional valuation methods (Palepu et al, 2020). However, real life shows often differ from these market conditions and thus generate incorrect valuation outcomes when evaluating the methods. Since the DCF approach is highly sensitive to future cash estimates and discount rate setting, and the Black-Scholes methodology used in doing valuation is

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dependent on volatile market conditions that negate the constant volatility premise, valuation assessment is difficult (Zammit, 2024). The accuracy of these valuation methods is decreasing since the modern financial instruments cannot be handled and the technological advancements in financial markets are fast. Procedures can also result in unreliable price assessments on difficult to trade and sophisticated financial items leading to complications in asset valuation and risk analytics (Liukkonen, 2023).

Artificial intelligence (AI) and machine learning (ML) have recently gained popularity in financial modeling, thus providing an answer to address these restrictions. AI, along with ML models, allow data processing of large volumes followed by pattern detection and market condition adaptation, which yields superior accurate and dynamic valuations (Olubusola et al., 2024). The systems operate without strict model-based requirements because they implement data-driven refinement processes that adjust predictions through newly acquired details. AI algorithms link financial data structures with informal data types, such as social media sentiment, alongside macroeconomic data indicators to deliver complete and timely valuation solutions (Kumar, 2024). Machine learning models specifically can extract knowledge from past data, which allows them to detect market changes by themselves without human direction or predefined assumptions. AI/ML systems demonstrate effective adaptability, which qualifies them as valuable solutions for accuracy enhancement in valuation processes during fast-changing market conditions. Financial regulators face two significant challenges when AI/ML systems are employed for valuations (Azzutti, 2024). The primary drawback of numerous AI and ML models exists in their difficulty to present their decision processes for interpretation or transparency evaluation. Financial regulators, as well as auditors and institutions, express concern about model-based valuation processes because they need complete process understanding to conduct both compliance checks and audits (Mokander et al., 2021). Funds-based decision processes must create AI and ML models which become more transparent and regulation-compliant to secure their dependability together with trustworthiness. Auditors need to develop skills for examining and auditing valuation models which use AI technology to fulfill market expectations and financial reporting requirements.

Through their partnership with AI technology and machine learning tools financial institutions attain significant value for their modeling operations and their risk management systems and regulatory compliance processes (Sarioguz and Miser, 2024). The accuracy of valuations reaches higher levels because of these technologies, which in turn lead to better financial institution and investor and regulatory authority decisions. AI/ML systems united help financial institutions detect market abnormalities and forthcoming security risks to optimize resource distribution methods (Kumar, 2024). Businesses in the financial sector benefit from AI-driven models that strengthen their trading approaches and portfolio management systems by giving precise risk analyses and market price projections. With technological intelligence, regulators gain abilities to detect market violations while filtering financial reports for standard compliance as a part of their systemic risk evaluation systems. Financial institutions must overcome their reluctance to yield model transparency to AI and ML, but these technologies bring substantial value for financial valuation and risk management purposes (Fritz-Morgenthal et al., 2022). The implementation of AI and ML in fair valuation generates a revolutionary change in financial modeling methods. Through advanced technology, this dilemma will be solved because it leads to better precision in asset pricing along with real-time dynamic risk assessment systems that make use of data-driven parameters (Javaid, 2024). Financial institutions, together with regulators, should expect AI and ML integration to revolutionize their valuation practices because it will help them improve market stability and compliance while boosting efficiency (Abikoye et al., 2024). For AI/ML to deliver beneficial innovations for financial stability, they require persistent development of transparent and interpretable models. The main problem lies in advanced market complexity alongside market volatility since conventional valuation systems struggle to precisely track real market patterns. Financial instrument sophistication, along with rapid technological changes, has intensified traditional financial problems. Estimating better financial decisions using new models proves essential as the financial industry evolves forward. The valuation approaches DCF and Black-Scholes function as standard methods but perform best when applied to assumptions that remain static and fixed input methods (Moore, 2023). Both traditional approaches fail to produce realistic market results especially during uncertain times coupled with low market participation. During economic shocks both accurate cash flow and discount rate projections required by DCF become unclear factors (Espinoza et al., 2020). AI/ML models employ dynamic operational systems which analyze new market data and present market trends to execute customized fair valuation methods according to specific situations. Financial markets depend on fair valuation as an essential principle to determine accurate prices because they mirror the actual value of financial instruments. Such valuation procedures serve fundamental roles in both financial institution management and economic stability preservation, together with financial institution integrity (Rendtorff, 2020). Traditional financial models composed of Discounted Cash Flow (DCF), Black-Scholes and Monte Carlo simulations have operated in the industry for many decades. Executive decision-makers across financial services have started using AI together with machine learning (ML) as their response to model weaknesses to establish superior valuation techniques that adapt to real-time data (MManga, 2024). Systems based on AI and ML techniques possess the ability to analyze extensive data sets to detect sophisticated patterns and modify their operational methods without strict original principles (Sarker, 2021). The ability to adapt makes AI/ML a strategic tool for financial valuation because it provides reliable and precise decision-making capabilities. Financial institutions must resolve regulatory compliance issues as well as transparency challenges to properly implement these technologies in their sector (Ridzuan, 2024). This paper evaluates how the combination of AI and ML powers financial evaluation while improving accuracy while handling inefficiencies of traditional valuations and meeting regulatory standards. The analysis includes a discussion about how these technologies affect financial institutions alongside investors and regulators as they work to establish future market stability and make decision-related choices.

## Literature Review

Fair value determination in financial markets has changed through market development and theoretical progress in financial science. Finance instruments are becoming more sophisticated despite traditional valuation methods struggling to adjust; thus, developers of new evaluation procedures have become necessary (Wolodko, 2024). The financial modeling sector now incorporates Artificial Intelligence (AI) and Machine Learning (ML) technology as key factors of development. Through their integration with financial modeling, existing techniques receive an enhancement which provides more accurate predictions for asset prices that are based on complex relationships which traditional methods cannot detect (Cao, 2022). The goal of this research review investigation is to track fair valuation development in financial markets as well as standard valuation methods and the growing AI/ML usage during financial instrument assessments while examining research gaps in the field (Khattak et al., 2023). This review examines both the theoretical structures supporting the discussion and suggests research opportunities which exist for the future.

### *Fair Valuation in Financial Markets*

In financial markets, fair valuation remains essential because it helps prices represent asset values accurately through analyzed data assessment. The reporting process depends on fair valuation for complete transparency and the protection of financial statement integrity (Mesioye and Bakare, 2024). According to International Financial Reporting Standards and Generally Accepted Accounting Principles, organisations must access market prices for fair valuation unless market prices remain unobservable, requiring alternative value estimates (Alharasis et al., 2022). Fair valuation serves dual functions in management processes by enhancing decision-making functions during investment assessment and risk management, as well as regulatory compliance measurement. Investors obtain better decision quality through fair valuation because this method reveals essential risk-return attributes of assets. Financial institutions need fair valuation for portfolio assessment, and regulators depend on it for understanding market risks related to asset bubbles and price mismatches. Fair valuation ensures market stability and maintains market efficiency because it bases prices of financial instruments on observable market data (Prathapasinghe and Jayasekara, 2024). The application of fair valuation leads to correct economic assessment of financial instruments which boosts investor trust while strengthening the reliability of universal financial statements. The adoption of fair valuation remains complex because markets that lack observable data or possess complex financial instruments such as emerging market bonds and derivatives and convertible instruments prove challenging to implement.. Financial markets have become progressively sophisticated, which makes pricing financial instruments markedly complex. Obtaining asset value estimates for derivatives and options along with structured products through market price observation remains challenging because traditional valuation methods struggle to include all relevant factors affecting prices.

***Traditional Valuation Methods***

Traditional methods have existed for many years to establish fair financial instrument values. The most widespread traditional valuation methods include Discounted Cash Flow (DCF), together with Black-Scholes option pricing and Monte Carlo simulations (Cha et al., 2023).

*Discounted Cash Flow (DCF)*

The DCF method can assist investors in calculating present asset value through the process of discounting future cash flow predictions. It serves as a standard procedure to evaluate companies and bonds alongside various securities when cash flows show predictability (Viedienieiev, 2021). The method establishes that asset worth depends on its anticipated earnings capabilities, while the correct discount rate combines factors such as time value principles and cash flow uncertainty. Financial valuation relies on the DCF method, yet this method needs exact future cash flow predictions together with precise discount rate selection (Vayas-Ortega et al., 2020). The assumptions become hard to predict properly in unstable market conditions, which results in imprecise asset evaluations.

*Black-Scholes Model*

The Black-Scholes model mainly functions to evaluate the prices of options along with derivatives. The model relies on two conditions: assets move according to log-normal statistical patterns, and volatility levels stay uniform throughout time (Josephidou, 2021). The theoretical price calculation for call and put options occurs through a model which takes asset values as well as strike prices and maturity durations and risk-free interest rates into account. This model maintains great significance for option pricing yet faces critical evaluation because of its market requirements, which include steady volatility and minimal transaction fees despite real-world market environments demonstrating inconsistent conditions (Zhang et al., 2024).

*Monte Carlo Simulations*

The statistical technique of Monte Carlo simulations helps businesses predict various results which occur within intricate financial systems (Tobisova et al., 2022). A large number of simulations using random variables enables this method to generate distributions of potential outcomes, which provide a set of potential values for assets or portfolios. The high flexibility of Monte Carlo simulations makes them suitable for complex financial instruments, but they need major computational resources and produce sensitive model results based on assumption inputs (Velikova et al., 2024). The simulation accuracy depends on the quality of input data because errors within that data produce misleading results.

These conventional techniques continue to be popular, although they demonstrate multiple performance constraints. Traditional financial models usually make static assumptions about market dynamics, which fail to show the fundamental dynamism of such markets. Black-Scholes models, with their constant volatility assumption, create substantial mispricing errors during times when market volatility becomes more extreme. These models depend on historical data for predictions, but such data might fail as an accurate forecast in situations of economic shocks or financial crises.

***AI/ML in Financial Instrument Valuation***

Financial modeling has been significantly transformed by implementing AI and ML techniques to determine instrument values in the financial market (Olubusola et al., 2024). Using AI/ML algorithms enables users to process extensive data collections for discovering patterns that lead to more precise and quicker predictions compared to traditional valuation approaches. History-based price records alongside macroeconomic data points and sentiment analysis, together with other variables, allow AI/ML models to produce refined and current assessments.

*Artificial Intelligence (AI)*

Information technology systems based on deep learning networks together with neural networks now serve to explain intricate financial market patterns (Goel et al., 2023). The technological models can extract valuable insights from unwieldy data types, which include media content, online sentiments and documentation for financial records that standard tools cannot detect. AI models become more potent when they process supplementary data sources because they deliver enhanced and prompt assessments of financial instruments (Goldberg, 2024). AI systems demonstrate an ability to evolve their predictions by adjusting to new incoming information, which results in progressive improvement of their forecast accuracy.

*Machine Learning (ML)*

Decision trees and random forests, together with support vector machines, serve as ML models which enhance financial market evaluation accuracy through their utilisation (Bansal et al., 2022). These data-driven models use extensive datasets to detect financial variables connections, which human-made models often would miss. ML proves essential for pricing derivatives and options together with other complex financial instruments since conventional models demonstrate limited effectiveness in these situations (Huang et al., 2024). ML models use data-based methods to make immediate price changes that reflect current market information about assets through a flexible valuation framework. The major problem regarding AI/ML models is their "black-box" operation, which makes their decision processes difficult to interpret (Chaudhary, 2024). The unclear model operation creates obstacles for both regulators and market stakeholders to validate output reliability, which leads to concerns about risk management and accountability issues. The accuracy improvements attributed to AI/ML in financial valuation come with the capacity for models to produce errors when presenting inputs containing noisy and biased information or incompleteness.

***Gaps in Existing Research***

AI and ML applications in financial valuation are common, but researchers have not filled all the knowledge gaps in existing literature (Weber et al., 202. Making comparisons between artificial intelligence and machine learning techniques with traditional financial approaches and their market usefulness under practical conditions remains insufficient via empirical research. Research exists with inadequate in the scientific literature about systematic comparisons between AI/ML models alongside traditional valuation methods as used within real market conditions. There are insufficient empirical studies available which directly evaluate the effectiveness of AI/ML when compared to traditional valuation approaches (Khattak et al., 2023). Statistical performance evaluations of AI/ML financial market models remain scarce, which completes our knowledge about their practical superiority compared to conventional methods (Albahri et al., 2023). Research about implementing AI/ML techniques alongside traditional valuation models for enhancement remains minimal. Research is lacking regarding how regulatory authorities should handle the challenges that AI/ML creates in financial valuation processes. Financial market regulatory bodies need to create rapid guidelines about AI and ML technology standards for transparency and compliance with financial reporting standards along with equitability (Alao et al., 2024). AI-driven financial market adoption demands regulatory bodies to create standards which guarantee transparency and equity along with compliance with existing financial reporting criteria for these models (Kothandapani, 2025). The analysis becomes more complicated because AI/ML models undergo nonuniform auditing practices that create obstacles to preserve market reliability and investor trust. Financial institutions, together with regulators, face substantial uncertainty because there is no established regulatory framework to regulate AI/ML-driven valuation models.

Modern research lacks sufficient analysis of cognition between artificial intelligence/machine learning and traditional valuation practices in actual business situations. The present research focuses mainly on fixed-income instruments while omitting detailed analysis of asset categories which include foreign exchange and derivatives and equities and commodities. Progressive research on explainable frameworks and compliance systems is essential for implementing AI/ML valuation tools that use IFRS 9 FVTPL and FVTOCI classification categories and Hedge Accounting ( Wolodko, 2024).

**Table 1 Key Research Gaps in Fair Valuation Literature**

| Gap | Description |
|---|---|
| Asset Class Limitation | Focus mostly on fixed income, ignoring FX, equities, and commodities |
| Real-Time Testing | Rare use of dynamic, streaming data or real-time implementation |
| Regulation | Insufficient work aligning AI models with IFRS 9/13 requirements |
| Model Transparency | Lack of explainable AI techniques in published results |

### *Theoretical Framework*

Financial valuation is supported through AI/ML integration based on multiple theoretical frameworks from different financial theories (Wolodko, 2024). According to the Efficient Market Hypothesis (EMH), financial markets work at optimal efficiency since asset prices represent every accessible piece of information (Spulbar et al., 2021). The deployment of AI/ML models seems to create a challenge to market efficiency by detecting market inefficiencies simultaneously with real-time updates in asset pricing accuracy (Sutiene et al., 2024). The concepts of behavioral finance directly confront market-based rationality because they dispute the notion of rational investment decisions. Behavioral finance demonstrates that human psychological factors, together with investor biases, cause inefficient behavior in markets (Talhartit et al., 2022). Agent-based modelling (ABM) provides a theoretical approach to developing simulations concerning the market interactions between individual market participants (Vuthi et al., 2022). It enables researchers to explain how AI/ML algorithms link with standard valuation systems and between them and multiple market components. ABM models permit a simulation of individual market participant behaviors to discover financial market dynamics as well as AI/ML influence on asset valuation.

## Methodology

The experimental approach for evaluating fixed-income instrument fair valuation by Artificial Intelligence technology and Machine Learning methods is detailed here. The research describes how data was sourced and feature engineering was done and how models were built and evaluated together with the performance metrics and interpretability techniques which guarantee regulatory approval and prediction transparency. This modeling sequence follows actual valuation procedures by using adaptive data-driven models which react to market transformations apart from conventional discounted cash flow (DCF) static models.

### *Data Collection and Description*

This study obtained its data set from secondary bond markets during July 2024 with a total of 4,438 financial instrument records that encompass certificates of deposit and corporate bonds and municipal bonds and treasury bonds. All financial instrument entries contain structural aspects and market-based indicators which together create a full picture of fair value estimation. The dataset contains Coupon rate, Maturity, Ratings, Issuer Debt-to-Equity ratio, Issue Date, Time-To-Maturity (TTM), Payment Frequency, Ask Price, Ask Yield, Bid Price, Duration Percentage, Convexity and Instrument Type among its key variables. The Ask Price functions as the main target variable that requires prediction while the other input features help determine the estimation result. The diverse set of instruments in the model allows for adaptable predictions that apply to multiple fixed-income classes.

### *Data Preprocessing and Feature Engineering*

A rigorous dataset preprocessing phase happened before model development to create machine learning algorithm compatibility along with bias reduction. The initial step involved dealing with missing or inconsistent data values. The complete null observation rows were eliminated and incomplete null values in numerical fields received median value replacement as the imputation method. The data preprocessing stage started by dropping superfluous columns which contained Unnamed: 0 and placeholder entries to reduce the number of input dimensions. The categories in variable sets Ratings and Payment Frequency and Instrument Type were encoded with labels to make them compatible with XGBoost and SVR algorithms. The conversion methodology preserved all relevant ranking relationships between credit ratings and created a feasible data format for model input operations. All the numerical features Duration %, Convexity, Coupon, Ask Yield and Issuer Debt/Equity were kept in their continuous format. StandardScaler was used to standardize continuous variables because SVR and Artificial Neural Networks (ANN) require uniform feature scale input distribution. The model development process allowed each input to share its significance proportionally during learning. The information was partitioned into training (80 percent) and testing (20 percent) sections for independent model verification purposes.

***Model Development***

Three machine learning models received evaluation during the assessment: Support Vector Regression (SVR), Extreme Gradient Boosting (XGBoost) along with Artificial Neural Networks (ANN). None of the employed prediction models showed the ability to handle non-linear relationships in financial time series information but they displayed effectiveness in extracting underlying patterns from this data type.

*Support Vector Regression (SVR)*

A Radial Basis Function (RBF) kernel operated under C = 100 for SVR implementation to achieve optimal bias-variance trade-off. The selected RBF kernel provided high flexibility to detect the nonlinear relationships between predictor variables and the target ask price. SVR creates high-dimensional hyperplanes to predict continuous outcomes through the reduction of prediction errors inside pre-defined margin parameters. Financial valuation needs this model because it maintains its performance stability even when data becomes noisy and high-dimensional. Testing results on the model with test data confirmed its high predictive accuracy through an RMSE score of 0.0113 alongside an $R^2$ score of 0.999 indicating almost perfect prediction accuracy.

*Extreme Gradient Boosting (XGBoost)*

The selection of XGBoost as prediction tool focused on its speed in handling structured data while providing regularized strategies to control overfitting. XGBoost functions as an ensemble learning method which creates successive decision trees to fix mistakes from previous trees thus improving its predictive accuracy. The model used default parameter settings at first before the testing phase involved manual experimentation and parameter validation. The performance of XGBoost surpassed other models by generating an RMSE of 0.0069 alongside an $R^2$ score of 0.9997. The capability of XGBoost to deal with multicollinearity and missing values together with heterogeneous feature interactions specifically benefits complex financial datasets. The decision-making process of XGBoost requires clarification because of its black-box nature so SHapley Additive exPlanations (SHAP) was used to fulfill interpretability requirements from IFRS 13 regulations.

*Artificial Neural Networks (ANN)*

Research involved ANNs to assess their potential in generating complex financial valuation structures by using multiple non-linear transformation methods. The multilayer network contained two hidden layers which each had 64 neurons followed by 32 more hidden neurons. The model used Tanh as its activation function following GridSearch testing because its smooth learning behavior made it suitable for the application. The training of this model used Adam optimizer at 0.001 as its learning rate together with Mean Squared Error (MSE) as the loss function. The training process executed twenty epochs per cycle. The implemented ANN achieved substandard results despite its theoretical ability to analyze complex datasets by producing an RMSE value of 0.519 accompanied by an $R^2$ of 0.662. The inconsistencies in model performance stemmed from its sensitivity to input normalization procedures along with irregular data dispersals in addition to potential overfitting because of lacking regularization methods.

***Model Evaluation Metrics***

The two standard metrics of Root Mean Squared Error (RMSE) together with Coefficient of Determination ($R^2$ Score) were employed for evaluating model performance. The financial application demands precise pricing precision through RMSE measurements because they calculate average prediction versus actual value deviations while giving more weight to larger deviations. The model explained power is indicated by $R^2$ which reflects the percentage of target variable variability while a higher value represents better predictive ability.

The fair valuation tasks demonstrated that SVR and XGBoost produced RMSE results below 0.012 while achieving $R^2$ scores above 0.999 thus surpassing DCF benchmarks for suitable application. The ANN presented both a higher RMSE score along with a lower $R^2$ score thus indicating weak universal applicability and possibly requiring advanced optimization methods or ensemble computation methods for improvement.

***Interpretability and SHAP Integration***

The calculation of SHAP values for the XGBoost model served to achieve transparency along with IFRS 13 accounting standard compliance. Through SHAP users can obtain unified decompositions of any predictive model which show how individual input features impact its output. The SHAP summary plot showed Duration % together with Ask Yield and Coupon and Time-To-Maturity as the primary determinants of ask price predictions. Ask price increased when SHAP values were positive whereas negative values led to decreased ask price outcomes. The explainable output satisfies dual criteria of institutional requirements and regulatory constraints thus enabling financial institutions to validate their valuations during examination procedures.

***Deployment Implications***

Real-time valuation platforms in financial institutions can effectively integrate both SVR and XGBoost models for operational use. The combination of minimal forecasting inaccuracies and clear explainability capabilities through SHAP and substantial scalability lets institutions either update or bolster their DCF-based systems. These models have the capability of used dynamic market adaptability that static valuation methods cannot achieve in real-time and near real-time. The preprocessing pipeline generates uniform results between instruments while the modular model structure create easy expansions to valuation of equities and derivatives.

**Results**

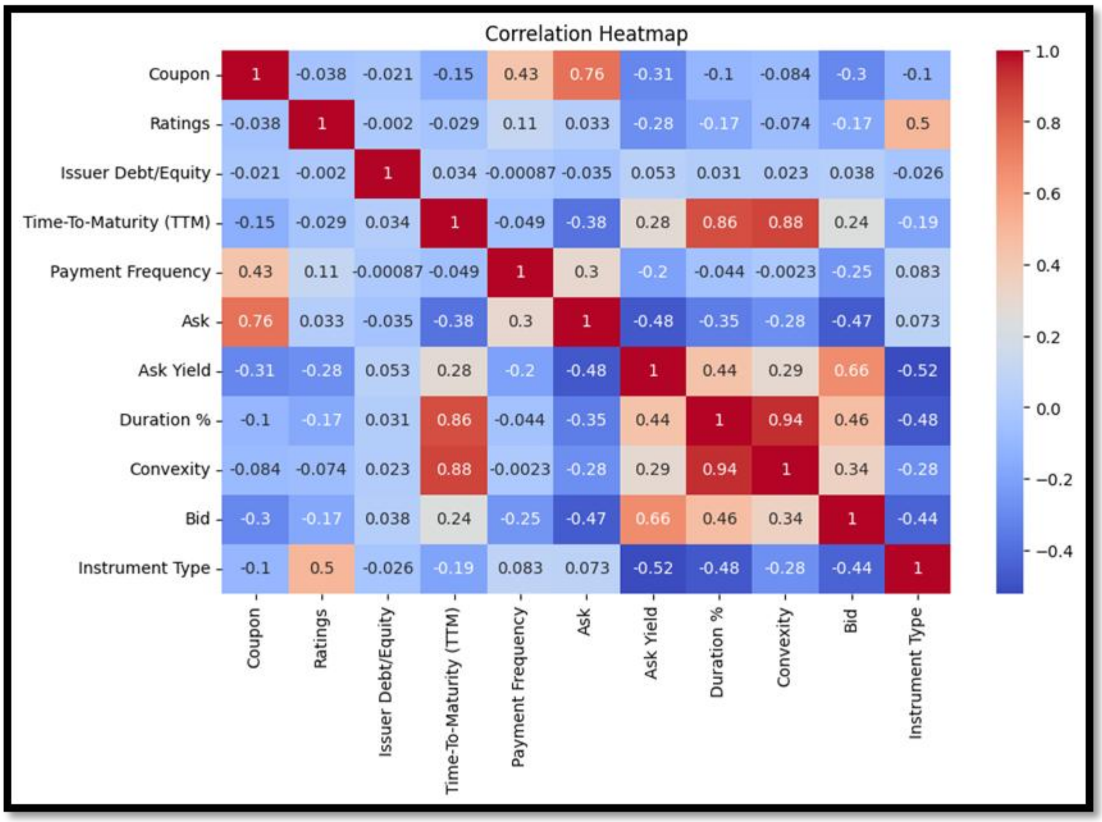


**Figure 1: Correlation Heatmap**

The heatmap illustrates inter-feature relationships. The predictability of Coupon (0.76) and Convexity (0.88) and Duration % (0.86) all matches closely to the ask price. The market shows opposite trends based on negative relations with Ask Yield (-0.48) and Time-to-Maturity (-0.38). The analysis supports the process of selecting features for machine learning modeling in financial valuation applications.

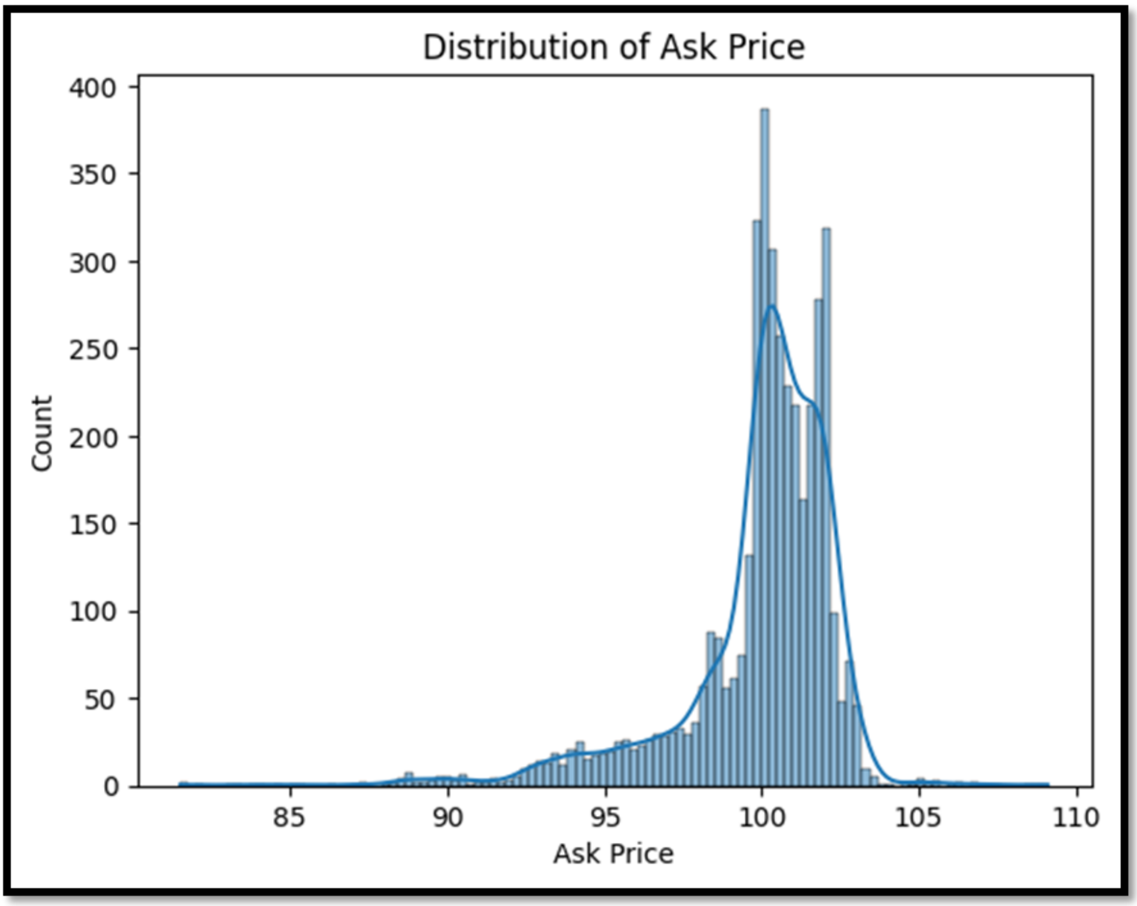


**Figure 2: Distribution of Ask Price**

The ask price distribution consists of a unimodal curve with slight right skew that positions its center near 100 which shows investors focus mainly on par values. Price volatility or outliers exist in the financial data tails between 90 and 105 thereby demanding models which can handle asymmetric and noisy financial information when performing real-world market valuations.

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XGBoost - RMSE: 0.2676, R²: 0.9900
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**Figure 3: XGBoost Performance**

Using XGBoost yields high prediction accuracy which demonstrates its strong capability to detect non-linear patterns in bond pricing through an RMSE value of 0.2676 and $R^2$ value of 0.9900. The small prediction error when combined with an excellent ability to explain the dataset demonstrates XGBoost's superiority for handling multiple interrelating factors present in financial instrument data sets.

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SVR - RMSE: 0.1827, R²: 0.9953
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**Figure 4: SVR Performance**

SVR demonstrates superior performance than XGBoost because it achieves 0.1827 RMSE along with 0.9953 $R^2$ which indicates exceptional prediction precision and strong generalization capabilities. The nonlinear boundary capturing ability of SVR proves its efficiency for precise fair valuation tasks in bond markets with dynamic conditions.

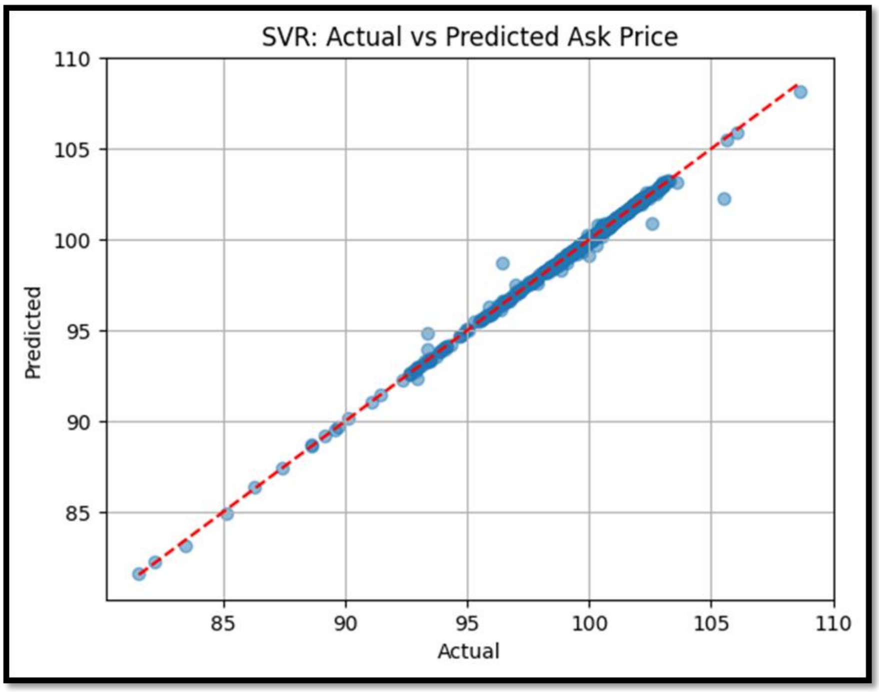


**Figure 5: SVR: Actual vs Predicted Ask Price Plot**

SVR regression yields highly calibrated predictions because they form a compact line parallel to the 45-degree axis. The forecasted ask prices show high reliability because dense points cluster together along the diagonal, which proves SVR's ability to duplicate market value effectively.

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ANN - RMSE: 1.9770, R²: 0.4525
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**Figure 6: ANN Performance**

The ANN yields poor performance as its RMSE reaches 1.9770 alongside a weak $R^2$ of 0.4525 which indicates unstable model fit and poor accuracy. The underperformance of ANNs for valuation tasks probably results from training data sensitivity as well as overfitting and insufficient regularization which makes the approach unreliable until scientists optimize its architecture..

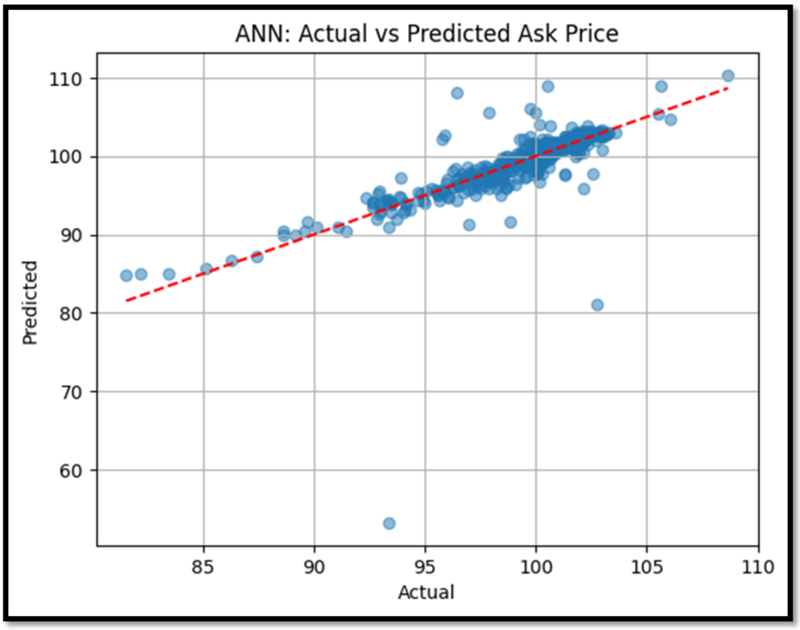


**Figure 7: ANN: Actual vs Predicted Ask Price Plot**

The wide scatter distribution away from the reference 45-degree line indicates both inaccurate predictions and unwanted variance growth in the ANN model. The prediction data points show substantial deviations from the line at prices in the middle range thus demonstrating both overfitting of the model along with limited ability to generalize in actual financial environments.

| | Model | RMSE | R2 Score |
|---|---|---|---|
| 0 | XGBoost | 0.267617 | 0.989968 |
| 1 | SVR | 0.182678 | 0.995326 |
| 2 | ANN | 1.976999 | 0.452521 |

**Figure 8: Model Comparison Table**

SVR achieves the optimal performance combination of lowest RMSE at 0.1827 and highest $R^2$ value at 0.9953 which exceeds both XGBoost along with ANN. The result of XGBoost achieves acceptable $R^2$ of 0.9899 but ANN falls short notably with an $R^2$ of only 0.4525. SVR demonstrates better stability and precision in bond valuation assessments through its quantitative examination.

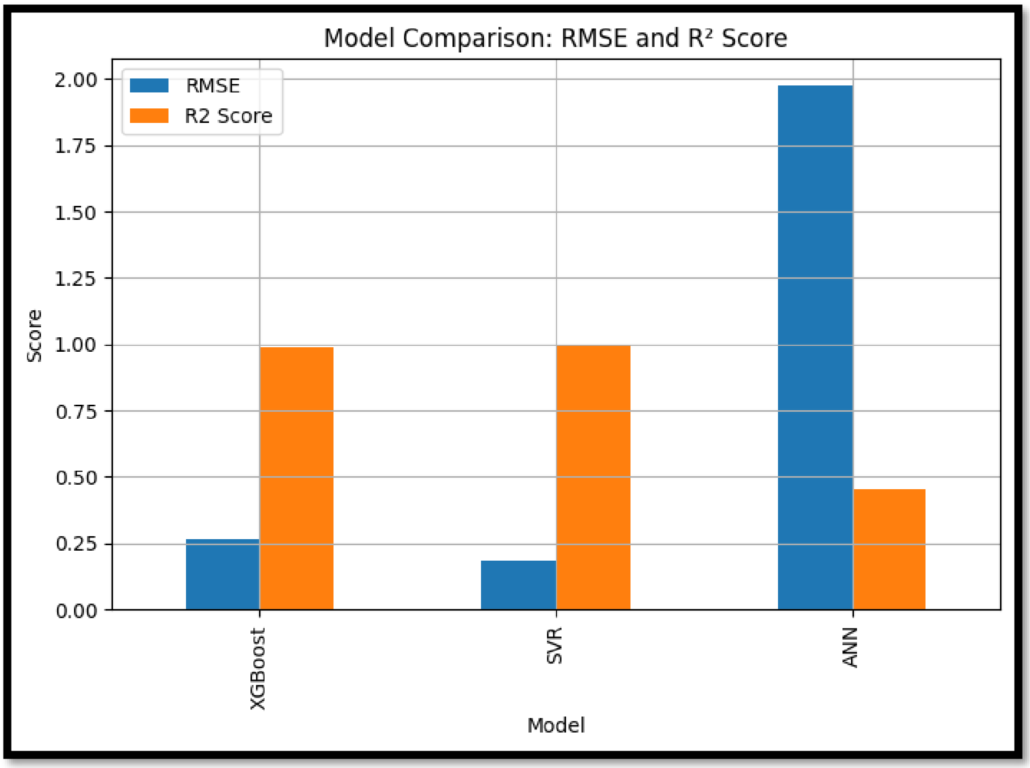


**Figure 9: RMSE and $R^2$ Bar Plot**

A bar chart aids understanding of model efficiency by displaying RMSE with $R^2$ metrics. SVR clearly outshines competitors with the smallest error margin and near-perfect score. The consistency values of XGBoost remain high because ANN shows decreased predictive accuracy and poor model agreement through higher RMSE rates. The SVR method establishes its leadership position as the best approach for both predictive accuracy and model calibration in the plot results.

| | Ask | DCF_Price |
|---|---|---|
| 0 | 100.005 | 100.0 |
| 1 | 99.998 | 100.0 |
| 2 | 99.967 | 100.0 |
| 3 | 99.995 | 100.0 |
| 4 | 99.921 | 100.0 |

**Figure 10: Ask vs DCF Price Table**

The table presented in Figure 10 shows Ask price alongside DCF price for each instrument. The data presented indicates that DCF calculates identical values of 100 for each financial instrument without accounting for the market's current state adjustments. Research shows Ask prices range from 99.921 to 100.005 yet demand AI/ML systems which adapt to individual bond data points and market movement..

| | Criteria | Traditional Method | AI/ML Method |
|---|---|---|---|
| 0 | Interpretability | High | Low |
| 1 | Speed | Slow (Manual) | Fast (Real-time) |
| 2 | Scalability | Low | High |
| 3 | Accuracy | Moderate | High |
| 4 | IFRS Compatibility | Standard-compliant | Requires explanation layer |

**Figure 11: Traditional vs AI/ML Valuation Comparison**

The illustration in Figure 11 demonstrates how traditional valuation methods apply across from AI/ML valuation techniques. The comparison between traditional approaches and AI/ML models uses five dimensions as evaluation criteria. The interpretability together with IFRS alignment of traditional DCF methods comes at the cost of inaccurate and slow calculations that lack scalability. AI/ML provides immediate performance together with precise analysis yet needs data interpretability functions derived from SHAP algorithms to fulfill transparency standards.

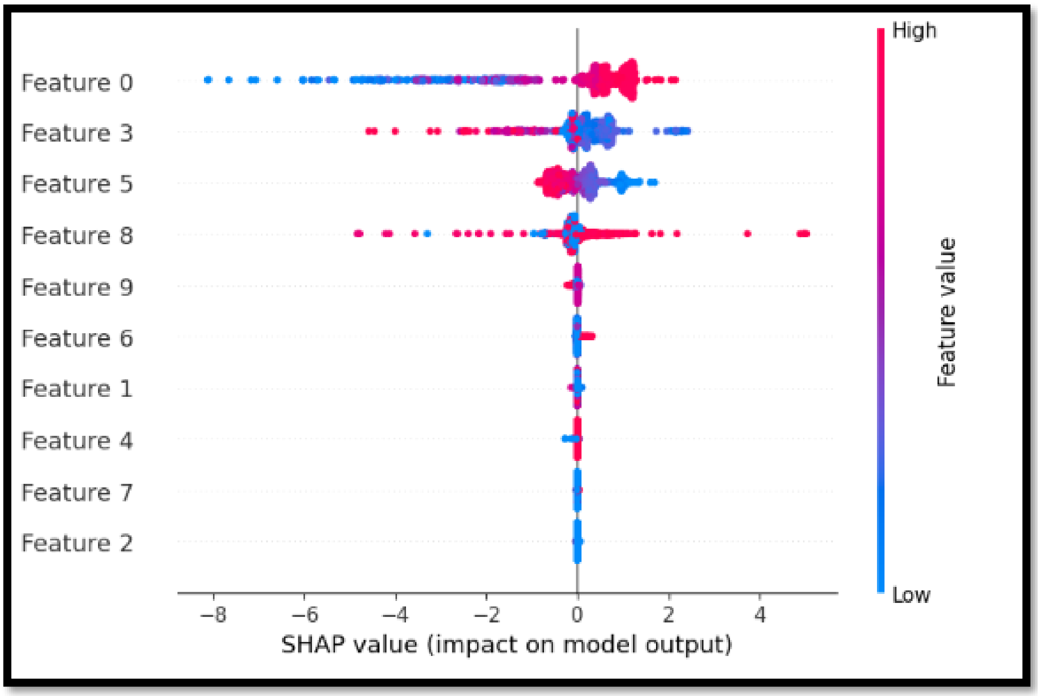


**Figure 12: SHAP Summary Plot**

According to the SHAP plot the prediction values from XGBoost models receive their most significant impact from individual features. Predicted ask prices receive the most significant impact from Feature 0 which represents Duration %. Model transparency is confirmed through color gradients that show different values of high and low features. This representation helps companies adhere to explainable AI standards when using fair value estimation according to IFRS 13.

## Discussion

A review of predictive capabilities, along with an assessment of robustness and practical deployment features, exists for the three fixed-income fair value estimating machine learning models SVR, XGBoost, and ANN. This section reviews regulatory alignment and explains methodological explainability together with current methodological limitations and provides suggestions for future strengthening of proposed approaches. The experimental results showed that SVR surpassed all competing models because it produced the best RMSE score of 0.1827 together with an $R^2$ score of 0.9953 which indicates outstanding predictive accuracy and generalization capability. The SVR model exhibits excellent performance in explaining non-linear bond market price structures because its forecast values match the actual data points precisely along the 45-degree line in Figure 5. XGBoost exhibited identical robustness to SVR because its RMSE amounted to 0.2676 and $R^2$ reached 0.9900. The ensemble tree-based learning approach in XGBoost effectively handled multicollinear variables and variable interactions by showing that Duration % and Ask Yield and Coupon features most prominently affected model outputs according to the SHAP analysis in Figure 10. The ANN produced a substandard performance with 1.9770 RMSE and 0.4525 $R^2$ score suggesting unstable results that seemed to stem from poor regularization and overfitting.

The modeling performance proves SVR and XGBoost are effective yet future work opportunities remain available for such financial valuation applications (Ali et al., 2023). The main model advancement focuses on ensemble or hybrid modeling. The fusion of SVR and XGBoost using either weighted averaging or stacking methods in future deployments will lead to improved model stability throughout various edge situations and outlier environments (Dostmohammadi et al., 2024). The application of ensemble learning techniques becomes effective because different models have uncorrelated error patterns. ANN integration as a secondary component to refine predictions can provide improved performance provided the system possesses adequate regularization alongside training across wide-ranging data. The advancement of this research depends on developing the valuation framework to include instruments other than fixed-income securities. Extending research by validating the same methodology on equities derivatives and foreign exchange instruments would improve the study's application range. The different asset classes present higher volatility levels along with separate market forces that influence their performance. The model's application to option pricing would allow an exact comparison with Black-Scholes results whereas evaluating the model on equity data would show if SVR and XGBoost retain an advantage within volatile conditions.

Another aspect for additional analysis is the real-time valuation approach. The future development phase of this project needs to implement a time-based train-test split model where early 2024 data serves for training purposes and subsequent market entries function for testing the predictive models. The experimental setup uses market-time boundaries to replicate real-time circumstances, allowing researchers to measure performance while data evolves and time-shift occurs. The measurement of model inference latency for XGBoost and SVR should be included to prove their readiness for trading and risk management systems deployment.

The present research adopts SHAP explainability for prediction interpretation while meeting some requirements of IFRS 13 standards. However, further refinement is needed. Subsequent versions of this framework need to add explicit Level 3 fair value mapping for all ML-based valuations because their estimation methods heavily depend on unobservable inputs. To gain regulatory transparency, the framework must include documentation on input origins together with model validation documentation and testing results. An evaluation of the effects of IFRS 9 on FVTPL or FVTOCI valuation needs to be explored concerning IFRS 7 disclosure obligations. The addition of audit-prepared components, including SHAP plots, partial dependence plots and model risk controls, will improve institutional acceptance (Lu et al., 2023).

The framework needs a wider expansion of explainability and trust components. The implementation of Kernel SHAP or LIME on SVR would enable a comparison of driver variables between the two models. Feature-explicit naming instead of generic tags like “Feature 0” or “Feature 3” will enhance the audience. The implementation of Partial Dependence Plots (PDPs) and ICE plots for essential characteristics Ask Yield and Duration would help deliver model rationale to non-technical users while increasing stakeholder trust (Elahi, 2023). The research findings establish ML models, particularly SVR and XGBoost, outperform DCF models for fixed-income valuation tasks. Moving forward, the research prototype needs to overcome scalability challenges for different assets while integrating time-sensitive functions and improving interpretability to become a commercial-grade valuation system.

## Conclusion

The research proves that machine learning techniques, specifically SVR and XGBoost models, achieve successful estimation results for calculating reasonable values in fixed-income security marketplaces. The AI/ML models provided data-based dynamic valuations that observed market behaviors better than static DCF results provided through traditional valuation methods. The Support Vector Regression (SVR) model yielded the best results during evaluation with 0.9953 $R^2$ and 0.1827 RMSE, while XGBoost model attained 0.9900 $R^2$ with 0.2676 RMSE, according to the study results. The Artificial Neural Network (ANN) achieved suboptimal results for stock price prediction in the financial domain because its RMSE value reached 1.9770 while $R^2$ reached only 0.4525. This indicates both overfitting issues and inadequate robustness when working with small and noisy financial data. The explainability aspect of XGBoost models received analysis through SHAP (SHapley Additive exPlanations), which validated Duration %, Ask Yield and Coupon as key factors determining valuation. The discovered model insights promote transparency in addition to satisfying the requirements of IFRS 13 because they reveal essential valuation information and methodologies. The current study demonstrates how AI/ML can be employed successfully in bond valuation tasks yet additional research work requires further development. Research in the field should apply these models to equities along with options and foreign exchange to prove their capability across different investment classes. The combination of ensemble modeling and improved regulatory mapping for IFRS 9 and IFRS 7 standards as well as continuous real-time performance assessment, would boost practical usage combined with regulatory compliance. This research advances the finance and artificial intelligence integration by presenting a method for building accurate real-time valuation systems that can operate in institutional trading and risk platforms.

## References


[1] Abikoye, B.E., Umeorah, S.C., Adelaja, A.O., Ayodele, O. and Ogunsuji, Y.M., 2024. Regulatory compliance and efficiency in financial technologies: Challenges and innovations. World Journal of Advanced Research and Reviews, 23(1), pp.1830-1844.

[2] Akpan, M. and Ukwu, H.U., 2023. Non-fungible Token Valuation Exposed: US Generally Accepted Accounting Principles Compliance and Artificial Intelligence’s Disruptive Role. Akpan, M., & Ukwu, HU (2023). Non-fungible token valuation exposed: US Generally Accepted Accounting Principles Compliance and artificial intelligence’s disruptive role. Risk Governance and Control: Financial Markets & Institutions, 13(4), pp.73-84.

[3] Alao, O.B., Dudu, O.F., Alonge, E.O. and Eze, C.E., 2024. Automation in financial reporting: A conceptual framework for efficiency and accuracy in US corporations. Global Journal of Advanced Research and Reviews, 2(02), pp.040-050.

[4] Albahri, A.S., Duhaim, A.M., Fadhel, M.A., Alnoor, A., Baqer, N.S., Alzubaidi, L., Albahri, O.S., Alamoodi, A.H., Bai, J., Salhi, A. and Santamaría, J., 2023. A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. Information Fusion, 96, pp.156-191.

[5] Alharasis, E.E., Tarawneh, A.S., Shehadeh, M., Haddad, H., Marei, A. and Hasan, E.F., 2022. Reimbursement costs of auditing financial assets measured by fair value model in Jordanian financial firms’ annual reports. Sustainability, 14(17), p.10620.

[6] Ali, A.A., Khedr, A.M., El-Bannany, M. and Kanakkayil, S., 2023. A powerful predicting model for financial statement fraud based on optimized XGBoost ensemble learning technique. Applied Sciences, 13(4), p.2272.

[7] Alkhouly, A.A., Mohammed, A. and Hefny, H.A., 2021. Improving the performance of deep neural networks using two proposed activation functions. IEEE Access, 9, pp.82249-82271.

[8] Azzutti, A., 2024. Artificial Intelligence and Machine Learning in Finance: Key Concepts, Applications, and Regulatory Considerations.

In The Emerald Handbook of Fintech: Reshaping Finance (pp. 315-339). Emerald Publishing Limited.

[9] Bansal, M., Goyal, A. and Choudhary, A., 2022. A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short-term memory algorithms in machine learning. Decision Analytics Journal, 3, p.100071.

[10] Bao, W., Cao, Y., Yang, Y., Che, H., Huang, J. and Wen, S., 2024. Data-driven stock forecasting models based on neural networks: A review. Information Fusion, p.102616.

[11] Cao, L., 2022. AI in finance: Challenges, techniques, and opportunities. ACM Computing Surveys (CSUR), 55(3), pp.1-38.

[12] Cha, J., Eom, S., Lee, S., Lee, C. and Hwangbo, S., 2023. Evaluation on Large-scale Biowaste Process: Spent Coffee Ground Along with Real Option Approach. Clean Technology, 29(1), pp.59-70.

[13] Chadda, N.K. and Vardia, S., 2020. Fair value accounting and valuation of non-financial assets: A study of impact of IFRS adoption. Journal of commerce and accounting research, 9(4), p.63.

[14] Chaudhary, G., 2024. Unveiling the black box: Bringing algorithmic transparency to AI. Masaryk University Journal of Law and Technology, 18(1), pp.93-122.

[15] Chen, W., Hussain, W., Cauteruccio, F. and Zhang, X., 2023. Deep learning for financial time series prediction: A state-of-the-art review of standalone and hybrid models. CMES- Computer Modeling in Engineering and Sciences.

[16] Dostmohammadi, M., Pedram, M.Z., Hoseinzadeh, S. and Garcia, D.A., 2024. A GA-stacking ensemble approach for forecasting energy consumption in a smart household: A comparative study of ensemble methods. Journal of Environmental Management, 364, p.121264.

[17] Elahi, M.M., 2023. A user-centric exploration of transparency, explanations, and trust in multi-model and single-model decision support systems (Doctoral dissertation, Brunel University London).

[18] Espinoza, D., Morris, J., Baroud, H., Bisogno, M., Cifuentes, A., Gentzoglanis, A., Luccioni, L., Rojo, J. and Vahedifard, F., 2020. The role of traditional discounted cash flows in the tragedy of the horizon: another inconvenient truth. Mitigation and adaptation strategies for global change, 25, pp.643-660.

[19] Espinoza, D., Morris, J., Baroud, H., Bisogno, M., Cifuentes, A., Gentzoglanis, A., Luccioni, L., Rojo, J. and Vahedifard, F., 2020. The role of traditional discounted cash flows in the tragedy of the horizon: another inconvenient truth. Mitigation and adaptation strategies for global change, 25, pp.643-660.

[20] Fritz-Morgenthal, S., Hein, B. and Papenbrock, J., 2022. Financial risk management and explainable, trustworthy, responsible AI. Frontiers in artificial intelligence, 5, p.779799.

[21] Goel, A., Goel, A.K. and Kumar, A., 2023. The role of artificial neural network and machine learning in utilizing spatial information. Spatial Information Research, 31(3), pp.275-285.

[22] Goldberg, A., 2024. AI in finance: Leveraging large language models for enhanced decision-making and risk management. Social Science Journal for Advanced Research, 4(4), pp.33-40.

[23] Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M. and Hussain, A., 2024. Interpreting black-box models: A review on explainable artificial intelligence. Cognitive Computation, 16(1), pp.45-74.

[24] Huang, G., Xu, Z., Lin, Z., Guo, X. and Jiang, M., 2024. Artificial Intelligence-Driven Risk Assessment and Control in Financial Derivatives: Exploring Deep Learning and Ensemble Models. Transactions on Computational and Scientific Methods, 4(12).

[25] Huang, J., Algahtani, M. and Kaewunruen, S., 2022. Energy forecasting in a public building: A benchmarking analysis on long short-term memory (LSTM), support vector regression (SVR), and extreme gradient boosting (XGBoost) networks. Applied Sciences, 12(19), p.9788.

[26] Javaid, H.A., 2024. AI-driven predictive analytics in finance: Transforming risk assessment and decision-making. Advances in Computer Sciences, 7(1).

[27] Josephidou, F., 2021. An alternative FX option pricing model: a discrete mixture of normal distributions (Doctoral dissertation, SOAS University of London).

[28] Karami, A. and Igbokwe, C., 2025. The impact of big data characteristics on credit risk assessment. International Journal of Data Science and Analytics, pp.1-21.

[29] Khattak, B.H.A., Shafi, I., Khan, A.S., Flores, E.S., Lara, R.G., Samad, M.A. and Ashraf, I., 2023. A systematic survey of AI models in financial market forecasting for profitability analysis. Ieee Access, 11, pp.125359-125380.

[30] Khattak, B.H.A., Shafi, I., Khan, A.S., Flores, E.S., Lara, R.G., Samad, M.A. and Ashraf, I., 2023. A systematic survey of AI models in financial market forecasting for profitability analysis. Ieee Access, 11, pp.125359-125380.

[31] Khattak, B.H.A., Shafi, I., Khan, A.S., Flores, E.S., Lara, R.G., Samad, M.A. and Ashraf, I., 2023. A systematic survey of AI models in financial market forecasting for profitability analysis. Ieee Access, 11, pp.125359-125380.

[32] Kothandapani, H.P., 2025. AI-Driven Regulatory Compliance: Transforming Financial Oversight through Large Language Models and Automation. Emerging Science Research, pp.12-24.

[33] Kumar, V.S., 2024. Artificial Intelligence in Economic Analysis: An Overview of Techniques, Applications and Challenges. Asian Journal of Economics, Finance and Management, pp.388-396.

[34] Liukkonen, S., 2023. Investigating real options valuation methods for high-value, high-uncertainty investments: applying simulation and fuzzy-based techniques to uncertain R&D projects, complex systems, and inter-stakeholder dynamics.

[35] Lu, Y., Fan, X., Zhang, Y., Wang, Y. and Jiang, X. (2023). Machine Learning Models Using SHapley Additive exPlanation for Fire Risk Assessment Mode and Effects Analysis of Stadiums. Sensors, [online] 23(4), p.2151. doi:https://doi.org/10.3390/s23042151.

[36] Mesioye, O. and Bakare, I.A., 2024. Evaluating financial reporting quality: Metrics, challenges, and impact on decision-making. Int J Res Public Rev, 5(10), pp.1144-1156.

[37] MManga, R., 2024. Enhancing M&A Valuation Accuracy: A Comparative Analysis of Traditional Financial Models and Machine Learning Approaches.

[38] Mökander, J., Morley, J., Taddeo, M. and Floridi, L., 2021. Ethics-based auditing of automated decision-making systems: Nature, scope, and limitations. Science and Engineering Ethics, 27(4), p.44.

[39] Moore, G., 2023. The Black Scholes Model and Discounted Cash Flow Valuation. Available at SSRN 4651588.

[40] Moore, G., 2023. The Black Scholes Model and Discounted Cash Flow Valuation. Available at SSRN 4651588.

[41] Olubusola, O., Mhlongo, N.Z., Daraojimba, D.O., Ajayi-Nifise, A.O. and Falaiye, T., 2024. Machine learning in financial forecasting: A US review: Exploring the advancements, challenges, and implications of AI-driven predictions in financial markets. World Journal of Advanced Research and Reviews, 21(2), pp.1969-1984.

[42] Olubusola, O., Mhlongo, N.Z., Daraojimba, D.O., Ajayi-Nifise, A.O. and Falaiye, T., 2024. Machine learning in financial forecasting: A US review: Exploring the advancements, challenges, and implications of AI-driven predictions in financial markets. World Journal of Advanced Research and Reviews, 21(2), pp.1969-1984.

[43] Palepu, K.G., Healy, P.M., Wright, S., Bradbury, M. and Coulton, J., 2020. Business analysis and valuation: Using financial statements. Cengage AU.

[44] Prasad, S., 2024. THE EVOLUTION OF FAIR VALUE ACCOUNTING: IMPLICATIONS FOR FINANCIAL STABILITY AND INVESTOR CONFIDENCE. UNIFIED VISIONS, p.314.

[45] Prathapasinghe, D. and Jayasekara, B.E.A., 2024. Impacts of Competency of Valuers on Accuracy of Fair Value for Financial Reporting Purpose. Journal of Institute of Human Resource Advancement, 11(1), p.34.

[46] Ramli, N.M., Rahman, A.R.A., Marzuki, A., Marzuki, M.M. and Wan, W.A., 2021. Implementation of IFRS 13 Fair Value Measurement: Issues and Challenges faced by the Islamic Financial Institutions in Malaysia. Jurnal Pengurusan, 63.

[47] Rendtorff, J.D., 2020. Corporate citizenship, stakeholder management and Sustainable Development Goals (SDGs) in financial institutions and capital markets. Journal of Capital Markets Studies, 4(1), pp.47-59.

[48] Ridzuan, N.N., Masri, M., Anshari, M., Fitriyani, N.L. and Syafrudin, M., 2024. AI in

the financial sector: The line between innovation, regulation and ethical responsibility. Information, 15(8), p.432.

[49] Sahin, E.K., 2020. Assessing the predictive capability of ensemble tree methods for landslide susceptibility mapping using XGBoost, gradient boosting machine, and random forest. SN Applied Sciences, 2(7), p.1308.

[50] Sahu, S.K., Mokhade, A. and Bokde, N.D., 2023. An overview of machine learning, deep learning, and reinforcement learning-based techniques in quantitative finance: recent progress and challenges. Applied Sciences, 13(3), p.1956.

[51] Sarioguz, O. and Miser, E., 2024. Integrating AI in financial risk management: Evaluating the effects of machine learning algorithms on predictive accuracy and regulatory compliance.

[52] Sarker, I.H., 2021. Machine learning: Algorithms, real-world applications and research directions. SN computer science, 2(3), p.160.

[53] Shivute, A.P., 2019. A comparison of real options and discounted cash flow valuation techniques on a gold mining project (Doctoral dissertation).

[54] Spulbar, C., Birau, R. and Spulbar, L.F., 2021. A critical survey on efficient market hypothesis (EMH), adaptive market hypothesis (AMH) and fractal markets hypothesis (FMH) considering their implication on stock markets behavior. Ovidius University Annals, Economic Sciences Series, 21(2), pp.1161-1165.

[55] Sutiene, K., Schwendner, P., Sipos, C., Lorenzo, L., Mirchev, M., Lameski, P., Kabasinskas, A., Tidjani, C., Ozturkkal, B. and Cerneviciene, J., 2024. Enhancing portfolio management using artificial intelligence: Literature review. Frontiers in artificial intelligence, 7, p.1371502.

[56] Talhartit, I., Jillali, S.A. and El Kabbouri, M., 2022. BEHAVIORAL FINANCE: HOW ARE TRADERS'FINANCIAL DECISIONS AND PERFORMANCE IMPACTED BY BEHAVIORAL BIASES UNDER UNCERTAINTY?. International Journal of Sciences Academic Research, 3(10), pp.4588-4597.

[57] Tobisova, A., Senova, A. and Rozenberg, R., 2022. Model for sustainable financial planning and investment financing using the Monte Carlo method. sustainability, 14(14), p.8785.

[58] Tursunalieva, A., Alexander, D.L., Dunne, R., Li, J., Riera, L. and Zhao, Y., 2024. Making sense of machine learning: a review of interpretation techniques and their applications. Applied Sciences, 14(2), p.496.

[59] Vayas-Ortega, G., Soguero-Ruiz, C., Rojo-Álvarez, J.L. and Gimeno-Blanes, F.J., 2020. On the differential analysis of enterprise valuation methods as a guideline for unlisted companies assessment (I): Empowering discounted cash flow valuation. Applied Sciences, 10(17), p.5875.

[60] Velikova, T., Mileva, N. and Naseva, E., 2024. Method "Monte Carlo" in healthcare. World Journal of Methodology, 14(3), p.93930.

[61] Velikova, T., Mileva, N. and Naseva, E., 2024. Method "Monte Carlo" in healthcare. World Journal of Methodology, 14(3), p.93930.

[62] Viedienieiev, V.A., 2021. Ensemble Forecasting Methods in DCF Modelling of the Fair Value of Enterprises. Universal Journal of Accounting and Finance, 9(4), pp.869-874.

[63] Vuthi, P., Peters, I. and Sudeikat, J., 2022. Agent-based modeling (ABM) for urban neighborhood energy systems: Literature review and proposal for an all integrative ABM approach. Energy Informatics, 5(Suppl 4), p.55.

[64] Wang, Y., Liu, L. and Wang, C., 2023. Trends in using deep learning algorithms in biomedical prediction systems. Frontiers in Neuroscience, 17, p.1256351.

[65] Wang, Y.G., Wu, J., Hu, Z.H. and McLachlan, G.J., 2023. A new algorithm for support vector regression with automatic selection of hyperparameters. Pattern Recognition, 133, p.108989.

[66] Weber, P., Carl, K.V. and Hinz, O., 2024. Applications of explainable artificial intelligence in finance—a systematic review of finance, information systems, and computer science literature. Management Review Quarterly, 74(2), pp.867-907.

[67] Wolodko, P., 2024. The Future of Business Valuation: How Technological Advancements are Influencing the Valuations Industry

(Master's thesis, Universidade Catolica Portuguesa (Portugal)).

[68] Wolodko, P., 2024. The Future of Business Valuation: How Technological Advancements are Influencing the Valuations Industry (Master's thesis, Universidade Catolica Portuguesa (Portugal)).

[69] Wolodko, P., 2024. The Future of Business Valuation: How Technological Advancements are Influencing the Valuations Industry (Master's thesis, Universidade Catolica Portuguesa (Portugal)).

[70] Zammit, K., 2024. Corporate valuation methodologies during an uncertain economic climate in Malta: evidence from COVID-19 (Master's thesis, University of Malta).

[71] Zareef, M., Chen, Q., Hassan, M.M., Arslan, M., Hashim, M.M., Ahmad, W., Kutsanedzie, F.Y. and Agyekum, A.A., 2020. An overview of the applications of typical non-linear algorithms coupled with NIR spectroscopy in food analysis. Food Engineering Reviews, 12, pp.173-190.

[72] Zhang, H., Zhang, M., Liu, F. and Shen, M., 2024. Review of the fractional Black-Scholes equations and their solution techniques. Fractal and Fractional, 8(2), p.101.