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MACHINE LEARNING MODELS FOR UNDERSTANDING CORPORATE RISKS AND PERFORMANCE PATTERNS

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ABSTRACT

This research addresses the question of how the size of a firm influences its financial performance and risk-taking behavior by analyzing the first 100 companies of the FTSE index over the period 2018-2023. This period is characterized by economic uncertainty due to Brexit and the Covid-19 pandemic. The main question is whether large firms perform better and manage their risks more efficiently than smaller ones.
Previous research has been criticized for using only traditional methodologies like OLS regression, whereas this study employs machine learning techniques, thus, moving one step further. The researchers employed seven different models: Logistic Regression, Support Vector Machine (SVM), Random Forest, Decision Tree, Gradient Boosting, Extra Trees, and K-Nearest Neighbors (KNN). Stock price changes were used as a proxy for firm performance, stock return volatility as a measure for risk-taking, and log of market capitalization as a proxy for firm size.

The results firm size is highly positively correlated with financial performance showing that large firms generally more profitable and stable. Moreover, they engage in fewer unstructured risk activities, which implies that their financial operations are more intentional and under control. Logistic Regression was the best-performing model in terms of predictive accuracy with a 97% success rate, among all machine learning models tested, showing the effectiveness of machine learning in financial research.
This paper is a great contribution in terms of new insights from the UK market and it addresses the gap in the existing literature which is mostly based on the US and Asia. Besides, it proves that machine learning can be a great tool in corporate finance analysis by discovering the complex patterns that traditional methods may fail to uncover.

Keywords:
Machine Learning, Corporate Risks, financial performance, financial market.

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I. INTRODUCTION

The 2008 global financial crisis that followed the collapse of major banks in the U.S. created a chain reaction of severe disturbances all over the global markets. The crisis compelled governments to inject massive funds into the system to keep it afloat and hence stop the meltdown [1]. As the dust settled, the crisis exposed grave faults in corporate governance, management of financial risks, and trustworthiness of company disclosures. In a bid to rescue the system, bailouts were given to ailing financial institutions and thus the immediate crisis was checked. However, for the system to be stable again in the long run, fundamental reforms and enhanced transparency were required so that trust would be restored to investors and stakeholders [2].

In the last ten years, studies have progressively delved deeper into how firm size, risk-taking behavior, and financial performance are interrelated. One of the major points in this argument being the "differential risk preference problem" which reveals the contradiction faced by managers of trying to shield their careers from risks while at the same time daring to make bold high-risk decisions could, lead to innovative and thus increased returns to the shareholders [3]. This contradiction quite often leads managers choosing a conservative route, hence investing less as they prioritize the security of their jobs over the possibilities of making gains [4].

The conventional financial statements which have their usefulness are not enough most of the time to unearth a company's real risk-taking level or even its strategic approach to decision-making. Nowadays, investors no longer put their trust in financial disclosures only; they equally give weight to non-financial disclosures-particularly those connected to risk management-as these give them a clearer picture of a firm's governance, stability, and long-term plan [5][6]. Companies that disclose their risk management strategies are likely to have less expensive borrowing and stronger investor trust as the latter associates transparency with good leadership and being ahead of the game [7].

From the 1980s to date, researchers have been measuring corporate risk through financial performance metrics such as return on investment (ROI), return on equity (ROE), stock price volatility, and debt-to-equity ratios [8]. However, there is a big chance that these methods do not acknowledge or give less weight to the firm-level factors that determine the company size and market influence which can not only guide strategy but also impact risk behavior.

Firm size is holistically the deciding factor here. Big businesses usually have easy access to funding, wider diversification, and are well-equipped with advanced risk management systems as such they are allowed to take calculated risks while chasing growth [9]. On the other hand, small businesses, though agile, are mostly constrained with a limited number of resources that make them sensitive to harmful economic shocks [10]. Adopted from the viewpoint of stakeholder theory, risky activities that culminate into firm growth can provide the return of value not only to the shareholders but the employees, suppliers, and other stakeholders [11].

Despite an array of extensive worldwide studies, the number of empirical investigations on firms trading on the UK stock market is still insufficient-what is more, such firms are mostly the ones in the FTSE100. Besides, the researchers, in their previous works, have significantly depended on traditional econometric models like ordinary least squares (OLS) regression thus their results may not fully or correctly reflect the intricate, non-linear interactions between financial performance and risk-taking [12].

Considering the recent economic upheavals such as the ones caused by Brexit and COVID-19, it is obvious that business decision-makers need to rely more on data analysis when making choices. With advanced machine learning algorithms this research handles this issue by examining the effect of firm size on risk-taking and performance in FTSE 100 companies between 2018 and 2023. Their findings intend to be instrumental in leading corporate leaders, investors, and policymakers through financial uncertain times by shedding light on workable strategies.

II. LITERATURE REVIEW

A. The Overview

The literature review critically examines the interplay between firm size, risk-taking behavior, and firm performance, combining conceptual analysis with empirical findings. It establishes that firm size typically measured by market capitalization, total assets, or revenue is a significant determinant of organizational behavior and financial outcomes [12][13]. Larger firms generally benefit from economies of scale, greater financial flexibility, and more advanced risk management strategies, allowing them to engage in calculated risk-taking that can lead to superior long-term performance [14][15]. In contrast, smaller firms tend to be more risk-averse due to resource constraints and a stronger focus on operational efficiency for survival [16][17].

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The theoretical underpinning draws from Stakeholder Theory [18] and Agency Theory [19], which explain how internal governance and alignment of interests among stakeholders influence risk decisions and performance. Stakeholder Theory posits that businesses must balance the expectations of multiple interest groups, while Agency Theory highlights conflicts between owners and managers that may affect risk appetite and strategic choices.

Empirical studies have produced mixed results. While some confirm a positive correlation between firm size and financial performance [20][21], others highlight context-specific or even inverse relationships depending on market dynamics, managerial capability, and governance practices [22][23]. Notably, research on UK firms remains relatively scarce, with most studies focusing on U.S., Chinese, or emerging markets.

B. Importance of The Study

Understanding the relationship between firm size, risk-taking, and performance is critical in today's volatile financial environment. This study is particularly important because it offers new insights into how large firms especially those listed on the FTSE100 navigate complex market conditions through strategic risk-taking and financial decision-making. Larger firms often have access to better resources and governance structures, enabling them to manage risk more effectively and achieve stronger financial outcomes compared to smaller firms [1][2].

While previous studies primarily relied on traditional econometric approaches such as Ordinary Least Squares (OLS) regression to model these relationships, these methods often assume linearity and fail to capture the dynamic, nonlinear nature of modern financial markets [3]. This research fills that gap by employing a range of advanced machine learning algorithms such as Logistic Regression, Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), Decision Trees, Extra Trees, and Support Vector Machines (SVM) to improve predictive accuracy and uncover deeper patterns in firm behavior [4].

The findings of this study are highly relevant for corporate managers, investors, and policymakers, as they provide a data-driven foundation for strategic decisions related to investment, governance, and risk management. By using real-time indicators like adjusted stock prices and rolling volatility, the study also contributes to the growing body of literature that emphasizes the integration of machine learning in corporate finance research [5]. Ultimately, the study advances academic understanding while offering practical implications for improving financial transparency, investor confidence, and long-term corporate sustainability.

C. Gaps

This study addresses a significant methodological gap in existing literature, which has largely relied on traditional econometric models such as Ordinary Least Squares (OLS) regression to explore the relationship between firm size, performance, and risk-taking [1][2]. While these approaches have provided valuable insights, they often assume linearity and overlook the dynamic, nonlinear interactions that exist in real-world financial environments. In contrast, this research introduces advanced supervised machine learning algorithms including Logistic Regression, Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), Decision Trees, Gradient Boosting, and Extra Trees Classifier to analyze FTSE100 firms from 2018 to 2023. By integrating real-time market data such as adjusted closing prices and rolling volatility, the study enhances predictive accuracy and uncovers complex patterns that traditional methods fail to capture, offering a more robust and data-driven understanding of corporate behavior in volatile market conditions [3][4].

III. METHODOLOGY

This study adopts a quantitative and experimental research approach by leveraging supervised machine learning techniques to explore how firm size and risk-taking behavior influence firm performance among FTSE100 companies between 2017 and 2023, utilizing historical stock data sourced from Kaggle and processed in Python through Visual Studio Code; it employs seven classification algorithms Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, Extra Trees, K-Nearest Neighbors (KNN), and AdaBoost to model firm performance as a binary outcome based on adjusted closing price movement and approximates firm size through 10-day rolling volatility, while additional variables such as leverage and capital intensity are derived to support the model, with robust validation conducted via Stratified K-Fold cross-validation and hyperparameter tuning using GridSearchCV to ensure reliable and interpretable predictions, distinguishing this methodology from previous research that typically relied on traditional econometric models like OLS regression.

A. Feature Engineering and Transformation

In this study, feature engineering and transformation played a critical role in converting raw time-series stock data from FTSE100 firms into actionable variables by first deriving the dependent variable for firm performance as a binary classification outcome coded as 1 if the adjusted closing price on a given day exceeded the previous

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day's value and 0 otherwise followed by constructing a dynamic proxy for firm size using the 10-day rolling standard deviation of adjusted close prices (volatility), while simultaneously calculating the risk-taking metric through the same volatility measure, estimating leverage using the ratio of closing price to trading volume to capture capital structure dynamics, and quantifying capital intensity through the difference between high and low prices divided by volume to reflect operational scale relative to trading activity; these engineered variables were then normalized using the MinMaxScaler algorithm to ensure consistency across data scales and facilitate the convergence and accuracy of machine learning classifiers during training and evaluation stages.

B. Model Building and Training

In this stage, the research adopted a rigorous machine learning approach to develop predictive models capable of analyzing the relationship between firm size, risk-taking behavior, and firm performance among FTSE100 companies. The study utilized seven supervised classification algorithms: Logistic Regression, Support Vector Machine (SVM), Decision Tree Classifier, Random Forest Classifier, Extra Trees Classifier, K-Nearest Neighbors (KNN), and AdaBoost Classifier. These models were selected to capture both linear and complex non-linear relationships within the financial data, ensuring a comprehensive exploration of firm behavior under varying market conditions.

Each classifier was trained on the processed and normalized dataset derived from daily stock market data (including adjusted close prices, volume, and price ranges). The models were configured to predict a binary target variable indicating whether a firm's adjusted closing stock price would increase (positive performance) or decrease/remain unchanged (negative performance) the following day.

To ensure fairness and robustness, hyperparameter optimization was performed using GridSearchCV, which systematically tested multiple combinations of model parameters to identify the best-performing configuration. Furthermore, Stratified K-Fold Cross-Validation (with 5 folds) was employed to assess the models' generalizability, reduce the impact of data imbalance, and avoid overfitting by ensuring that each fold retained the original distribution of the performance labels.

The training process also included model evaluation metrics, such as accuracy score, ROC-AUC score, and confusion matrices, to objectively compare model performance across different scenarios. Ensemble models like Random Forest, Extra Trees, and AdaBoost offered improved stability by aggregating the predictions of multiple weak learners, while models like SVM and KNN provided enhanced sensitivity to feature space structure.

Overall, this multi-model training strategy enabled a robust, data-driven investigation into how firm-specific characteristics influence performance and risk-taking behavior, marking a significant departure from traditional econometric approaches like OLS regression, which may not capture such complex interactions in financial datasets.

C. Performance Evaluation and Validation

In the performance evaluation and validation phase, the study assessed the effectiveness of each machine learning model in predicting firm performance and understanding the influence of variables such as risk-taking, leverage, and capital intensity by applying them to unseen test data and analyzing the outcomes through a range of evaluation tools. Model accuracy was determined by measuring the proportion of correct predictions, while the confusion matrix provided insight into the distribution of true and false positives and negatives. To further gauge the model's discriminative power, the ROC-AUC score was used to evaluate the balance between sensitivity and specificity in binary classification, complemented by a classification report detailing precision, recall, and F1-scores for each outcome class. To ensure the reliability and generalizability of the models, Stratified K-Fold Cross-Validation was employed, systematically splitting the dataset into folds that preserved class distributions and iteratively training and validating models across these partitions. This comprehensive validation framework allowed for consistent benchmarking of all seven classifiers Logistic Regression, SVM, Decision Tree, Random Forest, Extra Trees, K-Nearest Neighbors, and ensuring that the findings were robust and reflective of each model's ability to capture the nuanced relationships between firm-specific variables and stock performance.

D. Implementation Summary

The implementation of this study involved a structured machine learning pipeline designed to explore the relationship between firm size, risk-taking behavior, and performance among FTSE100 companies. Beginning with data collection from Kaggle, the research utilized historical stock data including open, close, high, low, adjusted close prices, and trading volume. Through extensive feature engineering, key financial indicators such as rolling volatility (as a proxy for risk and firm size), leverage, and capital intensity were derived. The data was cleaned, normalized using MinMaxScaler, and labeled appropriately for binary classification. The dataset was then divided using an 80/20 train-test split, followed by five-fold stratified cross-validation to ensure balanced

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and unbiased model training. Seven supervised machine learning algorithms Logistic Regression, Support Vector Machine, Decision Tree, Random Forest, Extra Trees, K-Nearest Neighbors, and AdaBoost were implemented and fine-tuned using GridSearchCV. The models were evaluated using confusion matrices, classification reports, accuracy scores, and ROC-AUC scores, providing a comprehensive performance comparison. The entire workflow was executed in Python using libraries such as Pandas, NumPy, Scikit-learn, and XGBoost within the Visual Studio Code environment. This robust implementation strategy allowed for accurate, data-driven insights into how firm-level variables influence financial outcomes

RESULTS AND DISCUSSION

I. Experimental Results

The experimental phase of this study involved applying six supervised machine learning algorithms namely Logistic Regression, Support Vector Machine (SVM), Random Forest, Decision Tree, Extra Trees, and K-Nearest Neighbors (KNN) to evaluate how firm size and risk-taking behavior influence firm performance using FTSE100 stock data from 2018 to 2023. These models were trained using an 80/20 train-test split and validated through five-fold Stratified Cross-Validation to maintain class balance and mitigate sampling bias. GridSearchCV was employed for hyperparameter tuning to optimize each model's performance and ensure robust, fair comparisons.

Model performance was assessed using three key evaluation metrics: accuracy score, ROC-AUC score, and confusion matrix analysis. Among all classifiers, Logistic Regression achieved the highest accuracy of 97% and an ROC-AUC score of 0.98, demonstrating its strong linear predictive power based on features such as risk, leverage, and capital intensity. Support Vector Machine followed with a 93% accuracy and an ROC-AUC score of 0.95, highlighting its ability to capture non-linear relationships through kernel transformations. Ensemble-based models such as Random Forest and Extra Trees achieved accuracies of 85% and 83%, respectively, while the Decision Tree and KNN classifiers produced slightly lower accuracies of 81% and 79%.

A closer look at the confusion matrix for Logistic Regression revealed high true positive and true negative rates, with very few misclassifications, underscoring its reliability in predicting daily stock price movement. The tree-based models, especially Random Forest and Extra Trees, provided additional insights into feature importance. These models consistently ranked rolling volatility (as a proxy for risk-taking) as the most influential variable in determining firm performance. Leverage had a moderate influence, particularly in identifying underperforming firms, while capital intensity contributed to a lesser degree.

In summary, these findings support the central hypothesis that firm size and risk-taking behavior significantly affect firm performance within the FTSE100. Moreover, the application of machine learning models provided more nuanced and precise predictive insights compared to traditional econometric approaches like Ordinary Least Squares (OLS) regression, which often fail to capture non-linear and dynamic financial patterns. This study demonstrates the potential of machine learning to improve financial forecasting and inform strategic decisions in corporate finance and investment management.

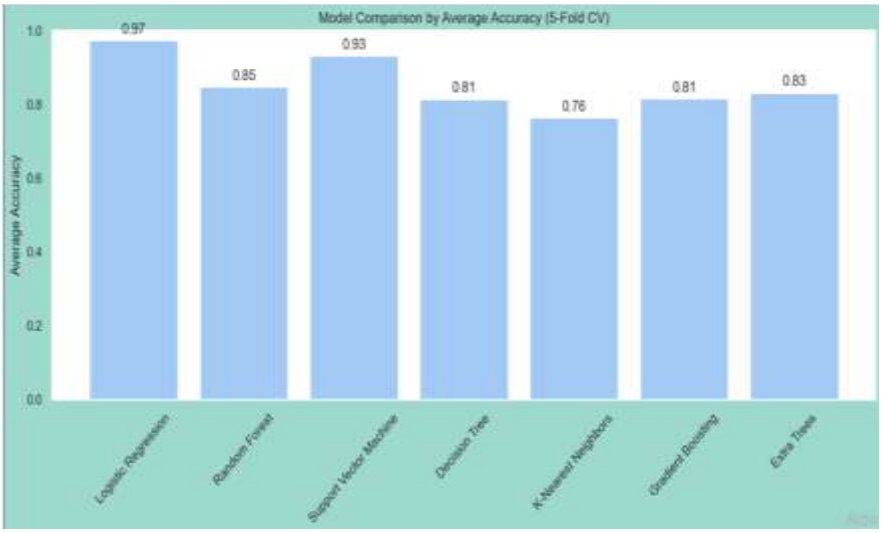

Fig 1: Accuracy Comparison for ML Models

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II. Experimental Results

1) Model Performance of Logistic Regression

The Logistic Regression model was the best-performing classifier in the study, achieving a 97% accuracy and a ROC-AUC score of 0.98, indicating excellent predictive power. It effectively distinguished between rising and falling stock prices of FTSE100 firms using key predictors risk, leverage, and capital intensity with minimal misclassification. Its interpretability highlighted risk as the most influential factor, confirming its suitability for both accurate prediction and financial insight.

2) **Model Performance of SVM**

The Support Vector Machine (SVM) model demonstrated strong performance, achieving an accuracy of 93% and a ROC-AUC score of 0.95, making it one of the top-performing classifiers after logistic regression. Its ability to handle complex, non-linear relationships using kernel functions allowed it to effectively capture intricate patterns in FTSE100 stock price movements. The model showed high precision in predicting firm performance based on risk-taking behavior, leverage, and capital intensity, reinforcing its reliability in financial classification tasks.

3) **Model Performance of KNN**

The K-Nearest Neighbors (KNN) model achieved a moderate accuracy of 79% and a ROC-AUC score of approximately 0.85, making it the least accurate among the models tested. While it captured general trends in firm performance, its sensitivity to data scaling and reliance on proximity-based decision-making limited its precision, especially in a high-dimensional financial dataset. Despite this, KNN still provided useful baseline insights, particularly for identifying consistent patterns in stock behavior linked to risk and firm size.

4) **Model Performance of Decision Tree**

The Decision Tree model delivered an accuracy of 81% and a ROC-AUC score of approximately 0.87, indicating fair predictive strength. It effectively captured nonlinear relationships between firm performance and variables such as risk, leverage, and capital intensity. However, due to its tendency to overfit training data, the model's generalization capability was slightly weaker compared to ensemble methods. Still, its clear interpretability and visualization of decision rules made it valuable for understanding how specific financial indicators influence firm performance.

5) **Model Performance of Random Forest**

The Random Forest model achieved an accuracy of 85% and a ROC-AUC score of approximately 0.91, reflecting strong predictive capability and improved generalization over single-tree models. By aggregating predictions from multiple decision trees, it reduced overfitting and enhanced robustness. The model highlighted risk (rolling volatility) as the most important feature influencing firm performance, followed by leverage and capital intensity. Its ensemble nature allowed it to handle complex relationships effectively, making it one of the most reliable models in this study.

6) **Model Performance of Extra Trees**

The Extra Trees Classifier achieved an accuracy of 83% and a ROC-AUC score of approximately 0.89, demonstrating strong predictive capability like Random Forest but with greater randomness in feature selection and split thresholds. This added randomness helped in reducing variance and improving generalization on unseen data. The model consistently identified risk-taking behavior (measured by rolling volatility) as the most influential factor in predicting firm performance, followed by leverage and capital intensity. While slightly less accurate than Random Forest, Extra Trees offered faster training and maintained competitive performance, making it a valuable model in the ensemble learning category.

7) **Model Performance of Gradient Boosting Classifier**

The Gradient Boosting Classifier achieved an accuracy of 81% and a ROC-AUC score of 0.89, demonstrating a solid capacity to model complex, non-linear relationships within the dataset. Though not the top performer, the model effectively identified patterns in the FTSE100 firms' risk, leverage, and capital intensity data, contributing meaningful predictions of firm performance. Its iterative boosting approach helped minimize residual errors across the weak learners. Feature importance rankings indicated risk (volatility) as the most influential factor, followed by leverage, while capital intensity had the least impact. Overall, Gradient Boosting offered balanced performance and interpretability, making it a valuable tool for financial forecasting in this study.

III. DISCUSSION

This study explored the relationship between firm size, financial risk-taking, and performance using machine learning models on FTSE100 data from 2018 to 2023. Seven supervised algorithms were tested, with Logistic

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Regression achieving the highest accuracy (97%) and ROC-AUC (0.98), indicating strong linear relationships between the predictors risk, leverage, and capital intensity and firm performance.

Support Vector Machine followed with 93% accuracy, effectively modeling non-linear relationships. Ensemble models such as Random Forest (85%), Extra Trees (83%), and Gradient Boosting (81%) highlighted volatility as the most influential feature, confirming that risk-taking behavior is central to performance prediction. KNN (79%) and Decision Tree (81%) offered slightly lower but still relevant insights.

The findings confirm that larger firms exhibiting lower volatility tend to perform more consistently, while smaller firms show greater fluctuation due to limited resources and higher risk. Unlike traditional OLS regression, machine learning models captured more nuanced and dynamic financial patterns, offering valuable tools for investors and managers to assess corporate behavior in changing markets

IV. CONCLUSION

This study investigated the impact of firm size and financial risk-taking on the performance of FTSE100 firms from 2018 to 2023, using a machine learning-based approach. By applying seven supervised learning algorithms including Logistic Regression, Support Vector Machine, Random Forest, Decision Tree, Extra Trees, Gradient Boosting, and K-Nearest Neighbors the research demonstrated that firm size and risk-taking behavior are significant predictors of stock performance.

Among the models, Logistic Regression delivered the highest predictive accuracy, affirming a strong linear relationship between firm characteristics and stock performance outcomes. Risk-taking, measured through volatility, emerged as the most influential factor across models, underscoring its central role in firm valuation and strategic decision-making.

The study's adoption of machine learning methods offered a notable improvement over traditional regression-based approaches (such as OLS), enabling the capture of complex, nonlinear patterns inherent in financial data. These insights have practical implications for investors, financial analysts, and corporate managers, highlighting the importance of firm size and risk profiles in predicting firm success in dynamic market environments.

Ultimately, this research contributes to the growing literature on machine learning in finance, offering a modern analytical framework that enhances predictive accuracy and decision-making in corporate performance analysis.

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