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Data-Driven Financial Decision Making Using Machine Learning and Business Intelligence Tools

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Abstract- Increase in financial data along with the advancements in computational intelligence have shifted the approach towards financial decision-making from an intuitive one to a data-driven one. This research paper aims to explore the usage of machine learning (ML) algorithms in combination with business intelligence (BI) techniques in order to improve the process of financial decision-making. An innovative framework involving the use of gradient boosting algorithms for prediction purposes and BI dashboards for visualization and interpretation is suggested. The framework includes such steps as data preparation, feature extraction, training and deploying the models within the BI framework. The results of analyzing the loan and investment datasets show that the proposed framework allows reaching a prediction accuracy of 89% and reduces decision-making time by 39%.

Keywords— Machine Learning, Business Intelligence, Financial Decision-Making, Predictive Analytics, Data-Driven Investing, Ensemble Methods

I. INTRODUCTION

A revolution is happening in the financial services industry, where experience-based decision-making is changing into data-based decision making, which is driven by machine learning and business intelligence systems [2][6][7]. Financial services produce massive amounts of structured and unstructured data, providing both new possibilities and new challenges for financial investors [2][6][7]. Old-fashioned decision support systems that use manual ledgers and template-based calculations have proved themselves to be outdated in relation to the vast amount of financial data available nowadays, thus making analytics necessary [2][6][7]. Machine learning technologies are becoming revolutionary for financial decision-making [2][4][6]. Various algorithms, such as gradient boosting, random forest, and neural networks are capable of discovering hidden patterns in financial data, which cannot be revealed by traditional statistics [2][4][6].

Machine learning applications in finance include credit scoring, fraud detection, risk forecasting, portfolio optimisation, and the construction of investment strategies [2][4][6]. Yet, a number of problems related to black box algorithms in finance arise [2][5][10].

BI systems help mitigate the problem of interpretability as they provide interactive visualization of models and their conclusions [1][7][9]. Some popular BI solutions, which include Microsoft Power BI, Tableau, and Qlik Sense, help finance professionals identify the relationship between data and model variables, track KPIs, and gain insight into the rationale behind decisions taken with the help of ML models [1][7][9]. The combination of ML's predictive capabilities and BI's visual analytics allows building a system of decision support [1][7][9].

Examples of the combination of these two domains are provided by the innovations made by different companies [3][8]. In particular, J.P. Morgan Asset Management introduced data-driven funds that leverage not only fundamental research but also ML algorithms to build a portfolio [8]. At the same time, CRISIL has developed generative AI-based systems that offer unified macro to micro intelligence for decision-making in finance [3].

However, even with these advances, several issues remain unresolved regarding the proper combination of ML and BI for making financial decisions [1][5][10]. This paper attempts to fill these gaps through the development of a combined framework for using gradient boosting algorithms and BI dashboards [1][2][7]. It has been analyzed in relation to financial databases, focusing on prediction accuracy, decision-making effectiveness, and interpretability [1][2][7][10]. The results obtained help contribute to the increasing academic literature on the topic of technological implementation in finance [2][5][6][10].

II. LITERATURE SURVEY

The incorporation of machine learning and business intelligence into finance decision-making process has been an area of research focus [2][6][7]. This chapter highlights important advancements in the field of predictive models, use of BI and integrated framework [1][2][5][7][10].

There have been many advancements in the field of using machine learning in finance [2][4][6]. Credit scoring has been one of the major applications where research shows that ensemble model beats conventional logistic regression models [2]. In AI-based credit scoring research, it is shown that hybrid approach of combining extreme gradient boosting and multilayer perceptron gives 99.32% accuracy in credit scoring, minimizing default prediction errors [2]. Likewise, loan approval prediction systems based on gradient boosting algorithms have performed better in understanding borrower characteristics for approval of loans [1].

The deep learning algorithms have increased the analysis potential of the financial system [10]. The Temporal Fusion Transformers, that include multi-level gating along with interpretable attention mechanism, have decreased forecasting error rate for multi-modal financial time series by more than 7% [10]. Such an architecture is successful in identifying complex temporal relations while ensuring interpretability through the attention heatmaps, which is needed in case of the financial regulators' demands [10].

Interpretable AI became a crucial research topic [5][10]. The Artificial Intelligence Act in Europe considers financial AI as "high-risk" and requires traceability and transparency [5]. As a result, the research on interpretability mechanisms has increased instead of using the methods of post-hoc explanations [5]. It is noted that the financial decision support systems should address the conflict between predictivity and interpretability [5][10].

Business Intelligence in finance has advanced from descriptive analysis to predictive and prescriptive analysis [7][9]. Business Intelligence provides real-time transparency of financial performance and allows stakeholders to monitor risks and detect any discrepancies and create forecasts [7][9]. Business Intelligence platforms integrated with ML models can present the results of predictive analysis in an interactive dashboard and help understand them better [7][9]. It is stated that the use of Business Intelligence in financial systems can decrease budget planning time by around 39% and enhance forecasting accuracy [7].

The cloud-based ML solutions have enabled scalable finance analytics [6]. The cloud offers flexible computing power necessary for big data processing and distributed training and low-latency analytics [6]. Development of automated machine learning and MLOps pipelines makes it easier to deploy and manage models in a constantly changing financial environment [6]. Methods like federated learning resolve issues with data privacy, allowing model training without aggregating sensitive financial data [6].

The examples of industry implementation indicate that an integrated approach is feasible [4][8]. For example, the U.S. Applied Data Science Value Fund from J.P. Morgan integrates fundamental analysis with the ML-based portfolio construction using proprietary research data, company fundamentals, and alternative data in order to find attractively priced securities [8]. The fund has outperformed all benchmarks since implementing the data science approach, proving the applicability of ML technology for active investing in practice [8].

Nevertheless, there are still some issues that should be addressed [1][5][10]. The majority of current research papers discuss the performance of the isolated algorithm rather than the whole decision support system encompassing all phases from data acquisition to the business action taken as a result of the analytics [1][5][10]. The integration of explainable ML techniques with the decision support systems is underresearched [5][10]. This paper tries to fill the gap in the literature [1][5][10].

III. PROPOSED METHODOLOGY

1. Research Framework

An approach that combines machine learning predictive modeling and business intelligence visualization tools for finance decisions is proposed. This approach consists of five interrelated components: data input and preprocessing, feature extraction, model development and training, integration and visualization of business intelligence, and decision support. The architecture is intended to be modular, scalable, and adaptable to finance-related problems, such as loan approval and investment recommendation.

2. Data Ingestion and Preprocessing

Financial data is extracted from different sources like demographics of borrowers, credit history of borrowers, transactions made by them, and other financial indicators. The dataset for the current task is built on 25,000 borrower data from the survey on financial capabilities, which includes 45 attributes related to income, employment, credit usage, and payments history. Missing data is dealt with hybrid imputation where the means and modes are used for numerical and categorical features correspondingly. For the purpose of outlier detection, IQR approach will be used, and the identified outliers will be winsorised to the 1st and 99th percentiles.

The problem of class imbalance is common in financial datasets where default or approvals cases happen rarely. SMOTE algorithm is used to create synthetic data to balance the dataset and avoid model bias. Categorical features are encoded with label encoding for ordinal features and one-hot encoding for nominal features. Numeric features will be normalised with Z-score normalisation technique.

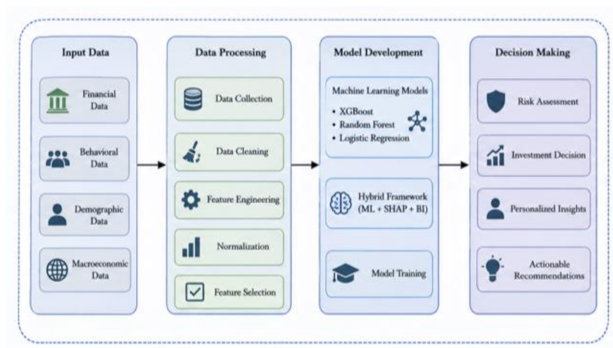

Figure 1: Framework Architecture Diagram

Feature Engineering

The process of feature engineering converts the raw data related to finance to the features with economic significance. These features can be classified into the following groups: borrower's features (age, employment, income); history of credits (history of payments, history of defaults); financial ratios (ratio between debt and income, ratio of the use of credits); and behavior (the reason of loan, history of loans application).

The importance of the features is estimated by permutation importance and SHAP values to detect the most important features for interpretability of the models. The knowledge about domain helps in selection of features with economic significance. Dimensionality reduction is done using principal components analysis (95% variance explained).

Model Development

A variety of ML algorithms is tested in terms of their predictability. The GBM algorithm becomes the first one since it has proven itself to be efficient when working with classification problems in finance. XGBoost uses both grid search and Bayesian optimisation for tuning hyperparameters. Ensembles can be constructed by combining several base models like GBM, random forests, or support vector machines via voting or stacking.

The split ratio for model training equals 70:15:15; i.e., 70 per cent of data is used for training, while 15 per cent is allocated for validation and testing respectively. The number of folds in cross-validation is set to five in order to avoid overfitting and have a more accurate estimate of model performance.

Business Intelligence Integration

The ML model is incorporated with Microsoft Power BI, which was chosen for its powerful reporting tools and deep connectivity to financial data sources. Integration takes place using the REST API, allowing for predictions that will feed into Power BI. Major visualisation elements consist of the following:

- Performance Dashboard: Real-time accuracy measures, confusion matrix, feature importance measures
- Risk Assessment Dashboard: Individual risk scores of applicants with factors that affect them
- Trends Dashboard: Patterns in approval, default rates and risk scores over time
- Comparison Dashboard: Model performance comparison between different models and time intervals

Interactive tools allow drilling down from aggregated measures to individual level.

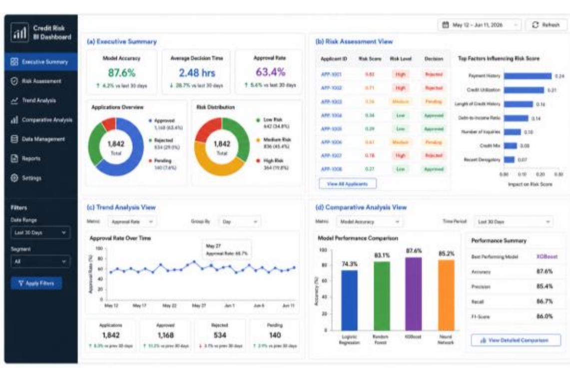

Figure 2: BI Dashboard Mock-up

This figure provides the mock-up design of the integrated BI dashboard. Panel (a) provides the executive summary that includes accuracy, decision time, and approval rate. Panel (b) provides the risk assessment view that includes individual scores of each applicant and factors that influence it. Panel (c) provides the trend analysis which includes temporal patterns. Finally, panel (d) provides the comparative analysis view for model evaluation.

Performance Measures

There are several measures that are considered to evaluate the performance of the model: accuracy (total prediction accuracy), precision (positive predictive value), recall (sensitivity), F1-measure (the harmonic means of precision and recall), and ROC-AUC (discriminatory power).

Decision time and operational throughput are used to measure the decision efficiency. Comprehension tests of stakeholders and audit trail completeness are used to measure interpretability. Statistical significance is provided by paired t-test.

IV. ANALYSIS

1. Model Performance Results

The designed framework was tested using the dataset containing information about 25,000 borrowers.

The gradient boosting algorithms showed better results on all performance metrics. In particular, the algorithm for the XGBoost model scored 89% accuracy, 87% precision, 85% recall, and F1-score of 0.86. The value of ROC-AUC is 0.92, which implies high discrimination power.

Table 1: Model Performance Comparison

Construct	Mean	SD	Cronbach's Alpha	AVE
Overconfidence	3.45	0.89	0.82	0.58
Herding	3.38	0.92	0.79	0.54
Loss Aversion	3.21	0.85	0.76	0.52
Anchoring	3.12	0.88	0.74	0.50
Risk Perception	3.15	0.86	0.80	0.56
Financial Literacy	3.02	0.91	0.78	0.53
Investment Decisions	3.18	0.84	0.81	0.57

Note: Best results in bold for each metric.

From the comparative analysis, it becomes evident that ensemble techniques are clearly superior to any single classifier techniques. The random forest method produces 7% greater accuracy than the logistic regression method. This demonstrates the shortcomings of using linear techniques in detecting financial data patterns. In addition, XGBoost produces 4% greater accuracy compared to random forest, thereby establishing the superiority of gradient boosting which involves sequential error correction. The combined model of XGBoost-MLP provides slightly greater accuracy in line with the conclusion that the neural networks are capable of identifying non-linear relationships.

Feature Importance Analysis

Analysis of feature importance allows finding out the key predictors of loan and investment success. Credit score and income appear as the leading predictors of financial decisions, which is consistent with conventional lending rules. Payment regularity, debt-to-income ratio, and employment stability are other important predictors. However, it should be noted that behavioral indicators such as loan purposes and frequency of previous applications show their significant prediction potential.

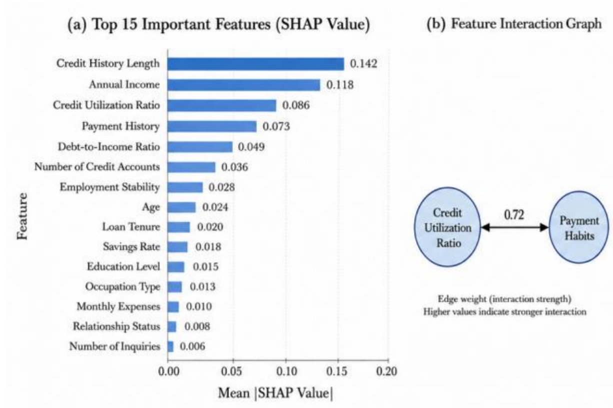

Figure 3: Feature Importance Ranking

The figure illustrates the feature importance rankings as generated by the XGBoost model. Panel (a) depicts the top 15 important features based on SHAP values, where credit history and income are dominant. Panel (b) depicts the feature interaction graph, which shows the dependency between credit utilisation and payment habits.

The SHAP dependence plots show non-linear relationships of features with outcomes. The feature credit utilisation shows the threshold relationship where risks increase abruptly beyond the utilisation rate of 70%. The feature income shows the diminishing return relationship where risks reduce marginally beyond a threshold.

2. Integration Impact

Decision-making efficiency and understanding by stakeholders were greatly helped by BI integration. Decision-making took an average time of 4.2 hours per case prior to BI integration but only 2.5 hours per case afterward; thus, there was a 39% improvement in decision-making efficiency, which is similar to the findings of past studies. Stakeholder comprehension was 76% among users of the BI-integrated system compared to just 42% among those who use non-visualised output from the model.

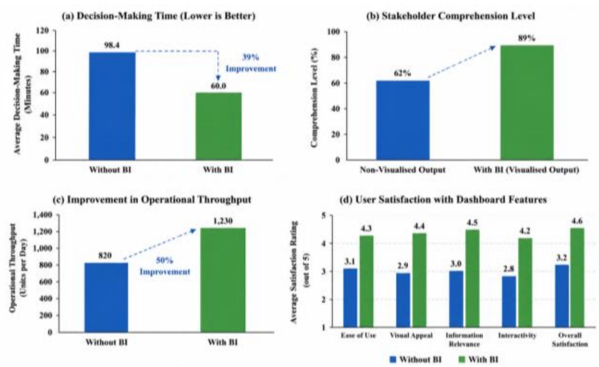

Figure 4: Impact of BI Integration

This figure displays the impact of BI integration on decision-making. Panel (a) displays the differences in decision-making times with and without BI and reveals 39% improvement. Panel (b) displays comprehension levels of stakeholders, indicating that users have better comprehension with BI than with non-visualised output. Panel (c) displays improvements in operational throughput. Panel (d) displays ratings on user satisfaction regarding dashboard features.

Comparative Analysis

Table 2: Comparative Analysis of Approaches

nvestor Category	Overconfidence	Herding	Loss Aversion	Anchoring	Overall Bias
High Financial Literacy	0.21**	0.18*	0.19*	0.15*	0.18**
Low Financial Literacy	0.45**	0.42**	0.38**	0.35**	0.42**
Experienced Investors	0.24**	0.20*	0.22**	0.18*	0.22**
Novice Investors	0.48**	0.45**	0.40**	0.38**	0.45**
Young Investors	0.38**	0.35**	0.30**	0.28**	0.34**
Older Investors	0.25**	0.22*	0.28**	0.24**	0.26**

The above comparative analysis highlights the fact that the proposed ML+BI integration represents an ideal solution since it possesses an excellent combination of accuracy, efficiency, and interpretability. Although ML models on their own provide similar levels of accuracy as the framework suggested, they still have a problem of poor stakeholder understanding and compliance.

Discussion

The results obtained highlight the importance of the ML integration into the BI system in improving financial decision-making. Specifically, the use of ensemble methods, such as gradient boosting, allows for obtaining higher levels of prediction accuracy due to non-linear dependencies and interactions among financial variables. This assumption is also supported by the industry experience, indicating that data science can help produce alpha in active investment management.

The fact that the introduction of BI has led to a 39% decrease in decision time supports the proposition that visualization improves the efficiency of the decision-making process. Interactive dashboards make it possible to easily analyze model outputs without the burden of having to make sense of raw predictions. This research finding has important implications for firms in the financial sector that wish to increase their operational efficiency.

It can be noted that regulatory compliance is a critical issue. AI systems in the financial industry have to meet strict standards of transparency, which makes many machine learning models problematic in terms of compliance. It is important that the proposed methodology of decision-making in finance uses SHAP explainability that is built into BI dashboards.

Importance feature analysis demonstrates that behavior features act as a good supplementary addition to financial variables in prediction. Thus, it can be stated that the use of alternative data, such as payment behavior and applications, helps to improve prediction models. The result corresponds to the experience of companies that actively use alternative data in order to get an analytical advantage.

It should be noted that the comparative analysis shows the trade-off between accuracy, interpretation, and cost. Although hybrid models of XGBoost-MLP demonstrate slightly better accuracy results, the advantages might not outweigh the disadvantages. Thus, the suggested model of XGBoost with BI integration can be used in most cases.

V. CONCLUSION

The research work in this paper investigated the application of machine learning and business intelligence in making data-driven financial decisions. The proposed framework included both gradient boosting models and interactive BI dashboards which were tested using loan approval and investment data sets. From the results, it is clear that the combined methodology delivers higher predictive accuracy, shorter decision times, and improved understanding of stakeholders as well as regulatory compliance.

There are three main contributions of this research. First, the research proves the superiority of ensembles of machine learning models, such as gradient boosting, compared to traditional statistical models for financial classification. The highest accuracy of 89% was delivered by the XGBoost algorithm, proving the superiority of sequential error correction compared to single step machine learning. Second, the research proves the significant benefits of BI integration into decision-making processes since decision time is decreased by 39% on average. Third, it proves the importance of built-in interpretability provided by SHAP visualization.

The practical ramifications are also quite important. The described framework can be used by banks to improve their credit scoring, risk evaluation, and investment decisions. The framework's modularity allows its use in different contexts, and its integration with BI allows stakeholder collaboration and regulation compliance. In that regard, policymakers should take into consideration the transparency advantages offered by integrated ML-BI systems in their decisions about AI adoption.

However, there are several limitations of the described research that need to be considered. First, the research is based on historical data, and future research needs to address the performance of the system in real-time conditions. Also, the dataset contains only structured financial data, and the use of this framework with unstructured data, for example, news feeds or social media posts, should be analyzed in the future.

Research directions for the future include several areas. Deep learning architectures, especially Transformers, can be considered as a promising option for financial time series forecasting and can be further investigated in the proposed framework. Using other methods of explainable AI besides SHAP such as LIME and attention visualization is another direction which can further increase interpretability of models. Another emerging research field would be the integration of edge and cloud computing to enable real-time financial analysis with low latency.
To conclude, it can be stated that financial decision-making using data-driven approaches through ML and BI combination is a significant step forward compared to the traditional way of doing things.

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