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Original Article

Integrating Explainable Artificial Intelligence and Statistical Process Control for Financial Forecasting and Risk Assessment

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Abstract

Effective economic decision needs accurate financial forecasting and risk assessment, which is crucial to ensure economic stability. The objective of this paper is to combine Explainable Artificial Intelligence (XAI) with Statistical Process Control (SPS) in order to improve financial modeling. Precise analysis of financial time series data is performed via Linear Regression, Random Forest Regressor, and eXtreme Gradient Boosting Regressor, wherein the various measures of accuracy of all three techniques are assessed by evaluating Mean Absolute Error, Mean Squared Error, Root Mean Squared Error, and R^2 Score.

In an effort to enhance explainability, SHapley Additive exPlanations and Local Interpretable Model Agnostic Explanation algorithms are adopted to interpret model results and assess the fundamental determinants of the financial outcome. SPS charts, including Shewhart, Cumulative Sum, and Exponentially Weighted Moving Average, are employed to track financial trends and identify anomalies in risk fluctuations. Additionally, hypothesis testing is performed to compare model predictions with actual financial indices. A calculus-based analysis explores derivative-based rate changes and integral-based cumulative trends in financial risk prediction.

A comparative analysis of XAI techniques is presented, providing insights into model performance. The results indicate that collaborative methods such as Random Forest and eXtreme Gradient Boosting surpass traditional regression approaches, while SPC and XAI enhance financial risk detection and improve the transparency of decision-making. This study highlights the importance of integrating XAI and SPC to achieve effective, interpretable, and data-driven financial forecasting.

Categories: Explainable AI, AI applications, Natural Language Processing (NLP)

Keywords: financial forecasting, explainable ai (xai), statistical process control (spc), machine learning, risk assessment, shap, lime, hypothesis testing, calculus-based analysis

Introduction

The essential components required for financial prediction and risk assessment are categorized as economic decision-making, market stability, and influencing investment strategies and policy-making. Traditional statistical approaches to designing financial models often struggle to adapt to nonlinear patterns in financial data, making it challenging to capture complex relationships and market dynamics efficiently [1]. However, due to developments in artificial intelligence (AI) and machine learning, financial prediction accuracy has significantly improved. Even so, the interpretability of Explainable AI (XAI)-driven methods and models continues to be a major problem, since models such

as ensemble methods and deep learning operate as "black boxes," making it challenging to comprehend how they make decisions [2]. This lack of transparency increases concerns regarding accountability and regulatory compliance in financial applications.

In order to improve the transparency and interpretability of machine learning models in financial procedures such as prediction and risk analysis, XAI has yielded vital solutions. SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), which are XAI methods, offer solutions for model predictions in financial forecasting to be utilized by stakeholders, regulators, and decision-makers [3,4]. The need for explainability in financial prediction is particularly relevant because of growing regulatory demands and the need to validate fair and unbiased decision-making [5].

Statistical Process Control (SPC) techniques, initially applied in industrial quality control, have increasingly found applications in financial risk evaluation and monitoring. SPC processes such as Shewhart Control Charts, Cumulative Sum Control Charts (CUSUM), and Exponentially Weighted Moving Average (EWMA) charts are applied for real-time monitoring of financial instabilities, early detection of anomalies, and deviations in trends.

The integration of XAI and SPC proposes a new technique for financial risk assessment that offers analytical accuracy with interpretability and real-time monitoring capabilities.

Objective of the study

The combination of XAI and SPC approaches is applied to enhance financial forecasting and risk evaluation. The supervised machine learning models,. Linear Regression (baseline model), Random Forest Regressor (ensemble model), and eXtreme Gradient Boosting (XGBoost Regressor - a gradient boosting model), are implemented.

The performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 Score, are computed for every supervised learning algorithm, and then a comparative analysis is performed to select the most suitable method.

XAI methods such as SHAP and LIME are applied to interpret model predictions. Hypothesis testing and calculus-based analysis are used to investigate financial trend changes and cumulative risk impact.

The key contributions and the complete process of achieving financial analysis and risk assessment are explained, as shown in Figure *1*.

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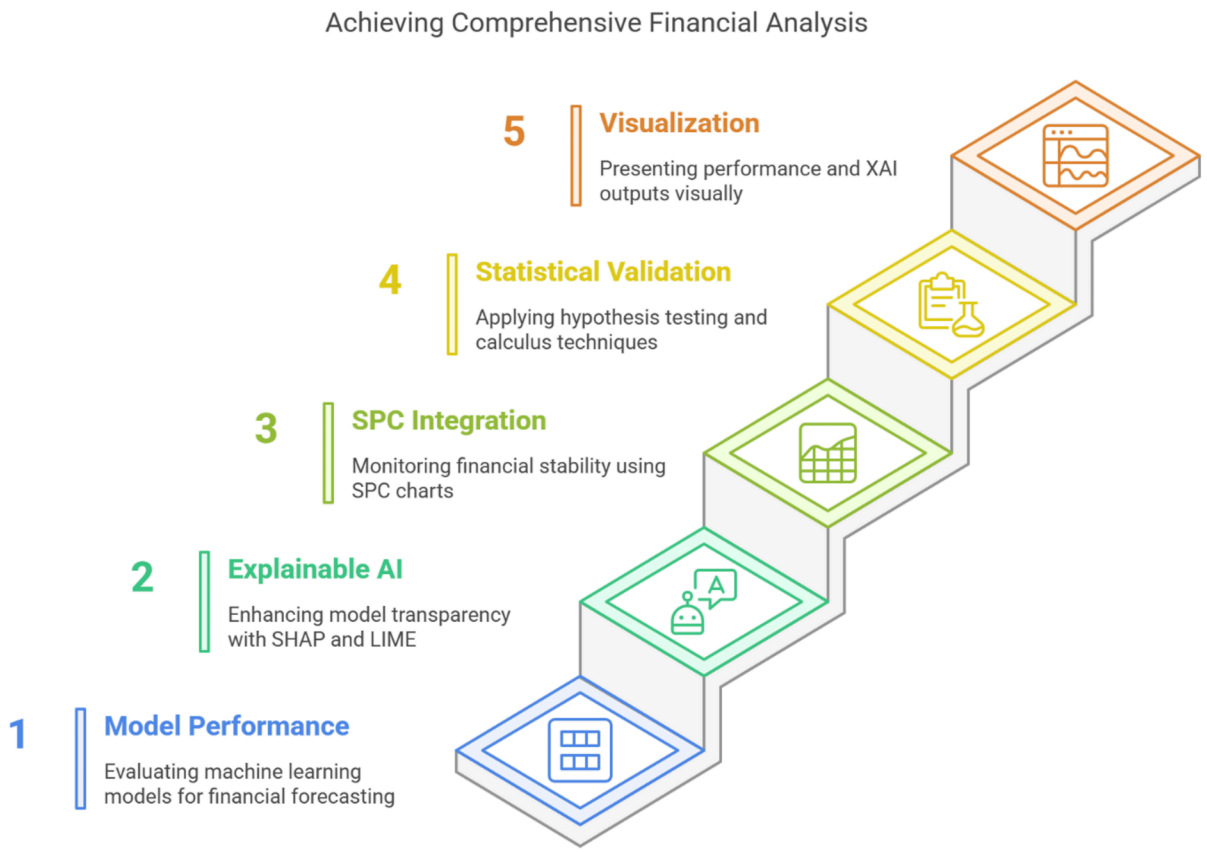


FIGURE 1: The figure presents an organized and planned approach that shows the integration of machine learning, XAI, SPC, and statistical validation for financial forecasting and risk assessment. The stepwise approach, showcasing the pictorial representation as a staircase, indicates a progressive methodology starting from data processing, model performance and evaluation, and extending to visualization.

LIME, Local Interpretable Model Agnostic Explanation; SHAP, SHapley Additive exPlanations; SPC, Statistical Process Control; XAI, Explainable Artificial Intelligence

Figure1 presents an organized and planned approach that shows integration of ML, XAI, SPC, and statistical validation for financial forecasting and risk assessment. The stepwise approach showcasing the pictorial representation as a staircase indicates the progressive methodology starting from data processing, model performance, and evaluation to visualization.

Step 1: Model Performance: The financial analysis and its foundation commences with assessing machine learning models of Linear Regression, Random Forest, and XGBoost. These techniques ensure the accurate prediction of financial trends and risks. The performance metrics like MAE, MSE, RMSE, and R^2 Score are calculated to evaluate accuracy and consistency.

Step 2: XAI: The supervised AI models tend to act as black boxes. SHAP and LIME are employed to enhance transparency. The techniques assist stakeholders, regulators, and financial analysts in understanding how the predictions happen, confirming fairness, accountability, and trust in AI-based financial decisions.

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Step 3: SPC Integration: Financial stability is tracked and monitored using Shewhart, CUSUM, and EWMA control charts. With the help of these techniques, anomalies, trends, and market fluctuations can be detected in real time, facilitating risk mitigation and early intervention.

Step 4: Statistical Validation: Hypothesis testing and calculus-based methods are used to validate financial models for additional improvement. Hypothesis testing confirms that identified trends and anomalies are statistically substantial, while calculus-based analysis (differentiation and integration) helps assess rate-of-change and cumulative financial dependencies over time.

Step 5: Visualization: The concluding step presents the results through comprehensive visualizations such as bar charts, trend lines, and tabular depictions. As a result, stakeholders can interpret model performance, comprehend risk factors, and make informed financial decisions.

The integration of XAI and SPC presents an innovative approach for financial prediction and risk assessment that enables improved interpretability and real-time anomaly detection. Since traditional financial models use only statistical techniques, and financial markets and their complexities are increasing every day, AI-based approaches need to be adopted. However, AI models suffer from the "black box" issue, which raises concerns regarding transparency and trust, making the combination of XAI methods such as SHAP and LIME vital for financial decision-making. SPC techniques such as Shewhart, CUSUM, and EWMA charts propose a structured framework for monitoring financial stability. To examine this study, the subsequent section explores existing research on financial forecasting, XAI methods, and the role of SPC in financial risk assessment, which will identify and highlight the research gaps.

Literature review

Financial forecasting has witnessed the use of traditional statistical models and AI-driven approaches in current research on market trends. Though AI improves prediction accuracy, its black box nature raises concerns about transparency. While XAI methods address this challenge, SPC methods provide a structured framework to monitor financial stability. This section reviews pertinent studies that highlight research gaps and key findings.

XAI in Financial Forecasting

Cerneviciene and Kabasinskas [1] explored the role of XAI in finance, analyzing various methods such as SHAP, LIME, and other rule-based methods. The proposed work in this paper highlights how transparency is improved in financial decision-making using XAI, predominantly in risk assessment and fraud detection. Commonly applied financial datasets are used and discussed in the paper. Findings suggest that integrating XAI boosts model interpretability, assisting regulatory compliance and trust. However, challenges such as computational complexity and the lack of standardized evaluation metrics exist in the proposed study.

XAI and machine learning applications in financial risk assessment using algorithms such as cluster-based K-nearest neighbor, cluster-based logistic regression, and cluster-based XGBoost are covered in a study by Senthil and Sree Kala [2]. These algorithms are mainly used for fraud detection, credit scoring, and stock market prediction. The stock market dataset is analyzed in the study, but referenced studies rely on financial transactions. The proposed work concludes that ML significantly improves predictive accuracy compared to traditional methods but highlights concerns regarding data bias and the opacity of complex models, thereby providing the necessity of XAI integration.

The importance of AI in financial risk management is reported, highlighting fairness, transparency, and regulatory compliance. It explores ethical AI frameworks and interpretable models, focusing on systems like SHAP and machine learning models. Findings from the paper provide the necessity of balancing AI performance with ethical considerations, but limitations include the absence of standardized guidelines and difficulty in applying fairness metrics across different financial domains [3].

Lundberg and Lee [4] explained the SHAP algorithm, which is a unified approach to machine learning model predictions. SHAP allocates feature importance scores using cooperative game theory, which improves interpretability and transparency across various financial models. Datasets from healthcare and finance are used in this AI-driven decision-

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making research. Results validate its efficiency in understanding model behavior; still, challenges include high computational cost, particularly for deep learning models.

A broad overview of XAI concepts, classifications, and challenges is provided by Barredo Arrieta et al. [5]. Here, XAI classifies methods into model-agnostic and model-specific categories. It does not focus on specific datasets but evaluates applications in finance, healthcare, and security. Key findings highlight the growing need for interpretable AI, with challenges including the trade-off between explainability and model performance. The study calls for standardized evaluation metrics and responsible AI frameworks but lacks empirical validation of the discussed techniques.

SPC methods, including Shewhart and CUSUM charts, are used to monitor the cryptocurrency market. Using historical cryptocurrency price data, it is validated that SPC effectively detects market anomalies. Also, certain forecasting methods for cryptocurrency volatility are suggested. Twelve common methods are compared, including Heterogeneous Autoregressive model, Generalized Autoregressive Conditional Heteroskedasticity, Least Absolute Shrinkage and Selection Operator, Support Vector Regression, Multi-Layer Perceptron, Random Forest, and Long Short-Term Memory. Findings indicate that SPC can serve as an early warning system for potential market manipulation. However, limitations include the method's sensitivity to extreme volatility and the need for domain-specific adaptation in financial applications [6].

The assessment and use of SPC in financial applications, comparing control charts such as Shewhart, EWMA, and CUSUM, is covered by Woodall et al. [7]. In the analysis of financial market datasets, it is found that SPC can detect structural changes and emerging risks. The study highlights SPC's advantages in real-time monitoring but notes its limitations in handling non-stationary financial data, requiring hybrid approaches with machine learning.

LIME, which is a method related to black-box machine learning models, produces locally interpretable models to estimate complex decision boundaries, which in turn enhances trust in AI predictions. This method is tested on numerous datasets that include financial fraud detection. The findings from the paper conclude that LIME improves transparency but is computationally expensive [8].

Computer Numerical Control is employed for SPC techniques in financial risk management that mainly focus on applications in financial trading and analysis of market trends. Using real-world financial transaction datasets, SPC validates and identifies abnormal patterns in trends effectively. The results propose that SPC improves financial monitoring, but the major challenge is its dependency on predefined thresholds. These thresholds may not adjust well to market conditions [9].

The requirement of interpretability in financial services, mainly for asset management companies subject to rigorous regulations, is highlighted by Weber et al. [10]. The research highlights that while AI can transform market analysis, there are numerous challenges due to its opaque nature. The study supports the integration of XAI to provide clear insights into AI-driven decisions, thereby facilitating compliance and fostering trust among stakeholders.

Machine learning-based explainable financial forecasting is the need of the day. Researchers address the non-linear dynamics of stock market prices by proposing AI-based prediction models. This method is used to enhance the transparency of predictions, enabling investors to understand the motivation behind AI-generated forecasts [11].

A new technique, the Interpretable Risk Assessment Framework with Belief Rule-Based Systems (IRAF-BRB), which uses XAI for risk assessments, is proposed by Badhon et al. [12]. This technique reduces the mean squared error using a BRB algorithm. The statistical significance of the results was set via a two-sample t-test, establishing IRAF-BRB as a dependable and effective tool for accurate and interpretable risk assessment.

An XAI framework for forecasting Bitcoin prices using feature selection integrated with SHAP explanations and daily financial and macroeconomic data is proposed by Goodell et al. [13]. The model accurately predicts price movements and identifies key inflection points, including the effects of the Russia-Ukraine war. The approach offers better accuracy, interpretability, and transparency compared to traditional methods. However, it is mainly applied to Bitcoin, requires high-quality data, and can be computationally demanding.

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SPC in Financial Risk Assessment

Basically, SPC techniques are mainly used in quality control analysis. However, in recent years, SPC has been adapted for financial risk assessment to keep track of and control financial processes. SPC techniques contribute to early warning systems and proactive risk management, since these methods detect variations and shifts in financial data [14].

There is a limited number of studies that provide integration of SPC and XAI in financial contexts; however, the application of SPC alone has revealed a promising approach. For example, control charts have been applied in monitoring financial time series data. This enables the detection of shifts and anomalies that may indicate emerging financial risks. The robustness of financial forecasting systems can be improved by providing continuous monitoring and validation of model outputs by combining SPC and AI models [15].

By monitoring price variations between Bitcoin and Ethereum, the research validates SPC's potential in detecting market anomalies and ensuring market stability. This is done by comparing price variations of Bitcoin and Ethereum [16,17].

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Reference	Technique Used	Dataset Used	Key Findings	Advantages	Disadvantages
Černevičienė and Kabašinskas [1]	Systematic review of XAI in financial forecasting	Review of 138 articles (2005-2022)	Integrating XAI and financial AI systems lead to more ethical and accountable financial practices	Identifies best practices in XAI for finance	Lacks empirical validation
Senthil and Sree Kala [2]	Cluster-based K-nearest neighbor, cluster-based logistic regression (LR), and cluster-based XGBoost	Stock market dataset and analysis using Hadoop	Categorization of XAI methods across financial domains	Provides a structured overview; aids in method selection	May overlook emerging techniques not yet widely studied
Fritz-Morgenthal et al. [3]	Discussion of AI/ML techniques (rules-based models, machine learning, deep learning, stochastic differential equation solvers) applied in financial risk management	Not applicable (conceptual/perspective paper, no experimental dataset used)	Increasing reliance on AI/ML in credit risk, insurance, anti-money laundering, fraud detection, and derivative pricing. Emphasis on the need for explainable, trustworthy, responsible AI. Suggests risk-based governance and testing framework for AI/ML models in finance	Comprehensive view across multiple financial applications. Highlights both opportunities and regulatory context (EU AI Act)	Lacks empirical validation with real datasets. Recommendations are broad and conceptual, not tested in practice
Woodall et al. [7]	Critique of SPC methods	Review of existing SPC methodologies	Highlights common pitfalls in SPC applications; provides recommendations for robust implementation	Offers practical guidance; emphasizes need for robust approaches	Theoretical focus; lacks empirical validation
Weber et al. [10]	XAI techniques for financial applications	Various financial datasets (stock markets, risk indicators)	XAI improves financial decision-making, transparency and governing	Enhances interpretability in AI-driven financial systems	Limited real-world implementation examples

			compliance in finance		
Arsenault et al. [11]	Machine learning models (XGBoost, LSTM) + SHAP, LIME	Stock market time series data	Address the non-linear dynamics of stock market prices by proposing AI-based prediction models	Improves model transparency and investor trust	High computational cost of XAI methods
Zhou et al. [16]	SHAP + Counterfactual Explanations in AI risk prediction	Global financial stability indicators dataset	SHAP and counterfactual descriptions enhance financial risk model interpretability	Improves regulatory compliance in risk models	Counterfactual explanations can be difficult to interpret
Wei and Dong [18]	Hybrid approach: Bayesian Networks (BN) + LR	CISA Known Exploited Vulnerabilities (775 vulnerability records)	The BN–LR hybrid achieved 97% accuracy and AUC ≈ 0.91, outperforming standalone BN and LR. It quantified causal relationships and highlighted CVSS score and exploit complexity as key risk drivers	Combines causal inference with predictive power. High accuracy and interpretability. Helps prioritize cybersecurity vulnerabilities effectively	Dependent on quality and coverage of vulnerability data. Requires expert knowledge for parameter estimation. May be complex to implement in real-world dynamic systems
Li et al. [19]	Explainable Case-Based Reasoning (CBR) with automated design	Financial risk datasets (not explicitly specified, applied in forecasting financial risk)	The explainable CBR system achieved strong prediction performance while providing natural economic interpretations. It reduces reliance on prior domain expertise compared to traditional CBR	High interpretability (transparent results). Good predictive performance vs. black-box AI. Reduces dependency on expert domain knowledge	Dataset details not clearly specified. May have limited scalability to highly dynamic or novel risk scenarios. Still less accurate than some black-box models in complex cases
Misheva and Osterrieder [20]	Conceptual framework for Domain-Driven XAI in financial time series forecasting	Not dataset-driven (conceptual guidelines, not empirical)	Suggests "good practices" for building AI-based forecasting systems, stressing the integration of domain expertise	Provides structured guidelines for responsible AI in finance. Encourages domain alignment and	No empirical validation on datasets. Recommendations are high-level and may be difficult to operationalize.

			with XAI to improve trust, transparency, and interpretability	interpretability. Bridges theory and practice conceptually	Adoption depends on future testing and application
European Banking Authority (EBA) researchers (as reported in Financial Times, 2023) [21]	Random Forests, Neural Networks, Ensemble Models for bank supervision	Supervisory ratios (breaches of concern levels) instead of actual bank failure data	Models can identify useful patterns in supervisory ratios, improving over past methods; ensemble approaches provide stronger performance	Better training data selection (concern-level breaches vs. failures). Potential to automate supervisory tasks. Shows measurable structure in financial stress indicators	Models are backward-looking ("rear-view mirror"). Cannot predict novel crises not in historical data. Gaps in regulation/data (especially non-bank financial institutions) limit coverage
Yeganeh and Shongwe [22]	Application of SPC in crypto markets	Cryptocurrency market data	Demonstrates SPC's potential in detecting market anomalies	Innovative approach; applicable to volatile markets	Limited to cryptocurrency; broader applicability needs exploration
Severin and Schmid [23]	SPC methods applied to financial time series; control charts (Shewhart, EWMA, CUSUM, residual charts, modified schemes) for GARCH processes	Stock market returns (empirical applications)	Control charts can effectively detect structural changes in financial time series modeled with GARCH. Residual-based and modified charts show different performance levels, with recommendations on parameter selection	Extends SPC methods from quality management to finance. Provides tools for monitoring volatility in returns. Offers early warning signals of structural shifts	Performance depends heavily on parameter choices. Assumes correct specification of GARCH models. May be less effective in capturing sudden, unprecedented market shocks

Yu et al. [24]	LLMs for explainable forecasting: GPT-4 (zero/few-shot inference), Open-LLaMA (instruction fine-tuning)	NASDAQ-100 stock price data, company metadata, historical financial/economic news	LLMs outperform traditional models (ARMA-GARCH, gradient boosting trees) by leveraging cross-sequence reasoning, multi-modal inputs, and inherent knowledge. GPT-4 gives the best results; fine-tuned Open-LLaMA provides explainable forecasts with reasonable performance.	Unifies textual + numerical signals in forecasting. Produces explainable, interpretable results. Outperforms classical methods. Demonstrates flexibility of LLMs in financial domain	GPT-4 access/cost may limit practical use. Fine-tuned open models perform weakly. High computational requirements. Generalization beyond NASDAQ-100 not validated
Stradi and Verdickt [25]	Experimental economics; incentivized choice experiments testing investor reactions to AI vs. human analyst forecasts	4 incentivized experiments with 3,400 U.S. participants	Investors on average show algorithm aversion – they respond less to forecasts when AI is mentioned, mainly due to lower perceived credibility. However, algorithm appreciation occurs among sophisticated investors, those with higher AI literacy, and politically progressive individuals	Provides causal experimental evidence on trust in AI forecasts. Highlights heterogeneity across investor groups. Relevant for practical applications in asset allocation and advisory services	Based on survey experiments, not real financial transactions. U.S.-only participants, which may limit generalizability. Short-term responses measured; long-term adoption not tested

TABLE 1: Literature review of selected papers.

XAI, Explainable Artificial Intelligence; AI/ML, Artificial Intelligence/Machine Learning; SPC, Statistical Process Control; LSTM, Long Short-Term Memory; SHAP, SHapley Additive exPlanations; LIME, Local Interpretable Model-agnostic Explanations; EWMA, Exponentially Weighted Moving Average; CUSUM, Cumulative Sum Control Chart; GARCH, Generalized Autoregressive Conditional Heteroskedasticity; ARMA, Autoregressive Moving Average; LLM, Large Language Model

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The application of SPC methods in financial market investigation has been explored by Yeganeh and Shongwe [22]. This study suggests an innovative use of control charts, mainly used for profile monitoring, to manage cryptocurrency markets. Table *1* summarizes key features of the discussed studies.

Materials And Methods

Data source and data collection

The data supporting this study are openly available in the World Bank Data Catalog at https://datacatalog.worldbank.org/search/dataset/0037996/statistical-performance-indicators, reference 0037996. The dataset used in this study comprises financial indicators and socio-economic stability indices obtained from the Data Catalog of the World Bank Group [26].

There are numerous challenges faced by national statistical systems. These challenges are due to the increasing requirement for reliable and high-quality data needed to update decision-making processes, combined with the continuously changing landscape of the data revolution. The World Bank has presented enhanced Statistical Performance Indicators (SPI) to evaluate the statistical performance of various countries that will build a strong learning mechanism amongst national statistical systems. The SPI highlights five vital features of a country's statistical performance, such as data usage, data facilities, data products, data sources, and data infrastructure. This novel method will be provided as a substitute for the Statistical Capacity Index (SCI), which the World Bank has been publishing regularly since 2004.

The dataset consists of 864 entries and 10 numerical columns.

SPI.INDEX - A complex index representing overall socio-economic stability. It serves as the target variable for financial risk prediction.

SPI.D5.1.DILG - Measures government efficiency and regulatory quality that affects financial stability and investor confidence.

SPI.D5.2.3.CNIN - Captures the level of corruption and institutional integrity, which impacts economic growth and financial markets.

SPI.D5.2.4.CPIBY - Represents the consumer irice index or inflation rate. It is a key macroeconomic factor influencing financial risk.

SPI.D5.2.6.EMPL - Reflects the employment rate, indicating labor market conditions that influence economic stability.

SPI.D5.2.8.FINA - Denotes financial sector development, assessing access to banking, credit availability, and overall financial inclusion.

SPI.D5.2.10.GSBP - Represents government spending policies, crucial for fiscal stability and macroeconomic planning.

SPI.D1.5.POV - Measures the poverty rate, providing insights into socio-economic inequalities and financial resilience.

SPI.D1.5.SAFE.MAN.WATER - Indicates access to safe and managed water, which is an essential infrastructure component affecting economic productivity and health.

SPI.D3.4.EDUC - Captures education levels and literacy rates, which influence workforce quality and long-term economic growth.

These components are important for financial stability and shown in Figure *2*.

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FIGURE 2: Illustration of key components influencing socio-economic stability, these factors collectively impact financial risk and economic flexibility.

Data exploration

A data frame is formed by loading the dataset, which allows for structured data manipulation. The preprocessing phase commences with handling missing values. This is done to ensure that incomplete records do not introduce biases or inaccuracies in the model's predictions. The target variable ("SPI.INDEX") is separated from the feature set, which allows the models to learn patterns from financial indicators and make meaningful predictions.

Standard scaler normalization is applied, which ensures numerical stability and avoids inconsistencies in data scales. This transformation homogenizes numerical features and ensures that no single variable excessively influences the machine learning models. In order to preserve data integrity and enable the models to be tested on unseen data, the dataset is finally divided into training (80%) and testing (20%) subsets. Preventing overfitting and verifying the generalizability of financial forecasting models depend on this step.

Histogram of SPI.INDEX

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The histogram provides a graphical representation of the target variable "SPI.INDEX", which is properly distributed. This plot provides an understanding of central tendency, spread, and shape. The presence of peaks in the histogram indicates where a large number of data points are concentrated, which helps reveal the distribution of the dataset. It also highlights potential skewness, outliers, or deviations from normal distribution, which are crucial in selecting appropriate machine learning models.

Correlation Heatmap

The correlation heatmap validates and visualizes the pairwise correlation coefficients between all features and the target variable. There is a normal range of correlation values from -1 to 1, in which values closer to 1 represent a strong positive relationship, while values closer to -1 represent a negative relationship. Such visualizations are vital in the selection of features as they pinpoint characteristics that have a greater impact on the target variable. This heatmap also helps identify multicollinearity between features, which would have an impact on regression model performance.

Residual Plot

The residual plot provides the difference between actual and predicted value, called as residuals, and visualizes them. This plot helps to evaluate the model assumptions of linearity and constant variance of residuals. Preferably, the residuals should be randomly scattered around zero without forming any systematic patterns. Any visible patterns or trends in the residual plot may specify that the model is not sufficiently capturing certain relationships within the data, which requires further model refinement.

Error Distribution Plot

The error distribution plot provides the distribution of prediction errors and provides perceptions of the accuracy and performance of the model. The spread and shape of the error distribution help determine whether the model methodically overestimates or underestimates the target variable. A narrow and symmetric distribution centered around zero suggests that the model is performing well, while a wide or skewed distribution indicates that the model's predictions have higher variance.

The complete data preparation process is explained with the help of Figure *3*.

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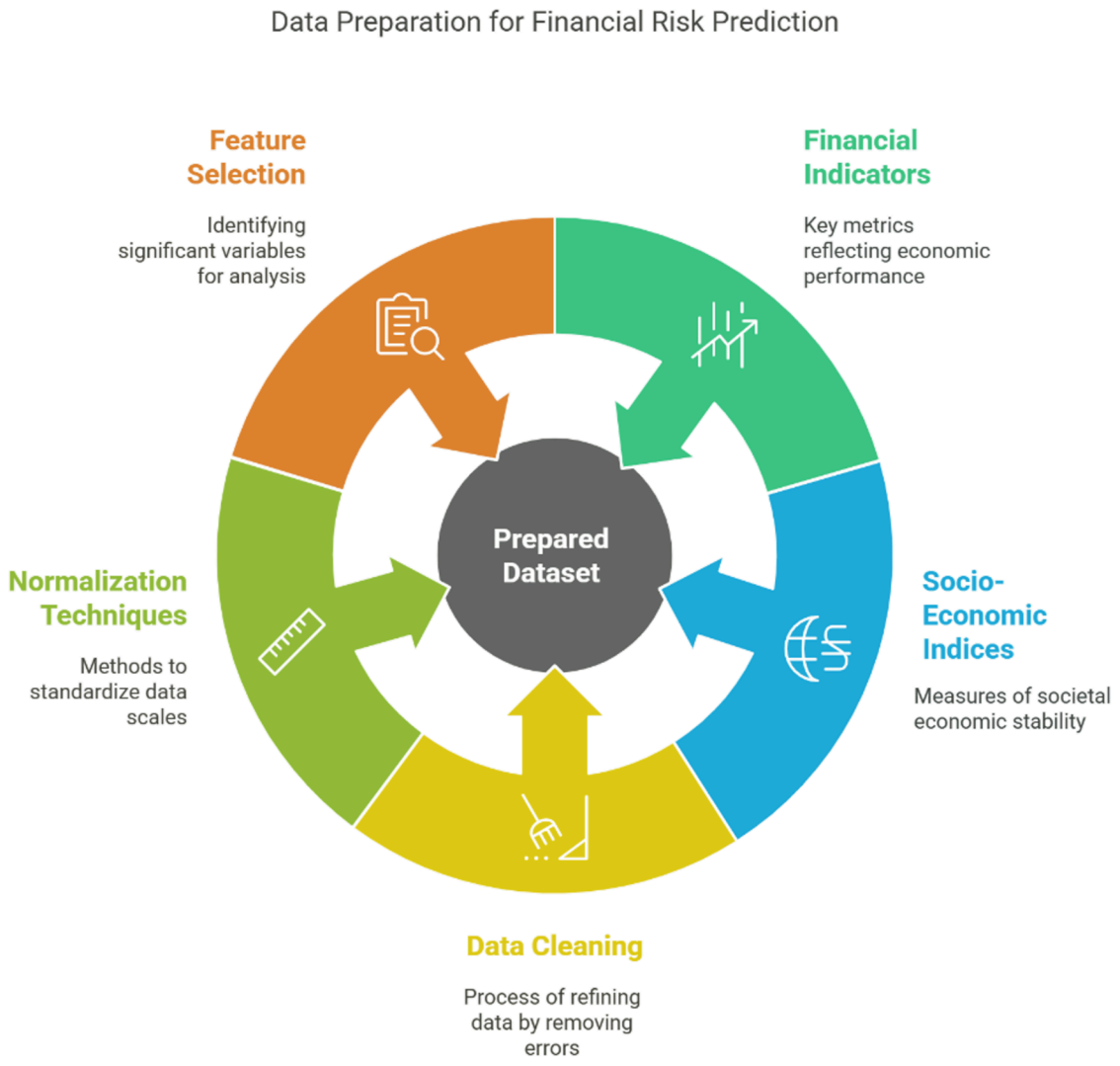


FIGURE 3: Steps for data preparation for Financial Risk Prediction. The figure demonstrates the key stages in preparing a dataset for financial risk prediction. The essential component, "Prepared Dataset," is obtained through five critical processes: (i) Feature Selection: that identifies significant variables for analysis, (ii) Financial Indicators: integrating key metrics reflecting economic performance, (iii) Socio-Economic Indices: considering measures of societal economic stability, (iv) Data Cleaning: refining data by removing errors, and (v) Normalization Techniques: standardizing data scales to ensure consistency. These steps collectively improve the dataset's quality and reliability for financial forecasting and risk assessment.

The proposed methodology integrates XAI with SPC to boost financial forecasting and risk assessment. This approach will ensure model interpretability, improve predictive accuracy, and empower real-time monitoring of financial stability. The methodology consists of several key stages, as explained in the subsequent sections. The complete process is discussed in detail with the help of a diagram, as shown in Figure *4*.

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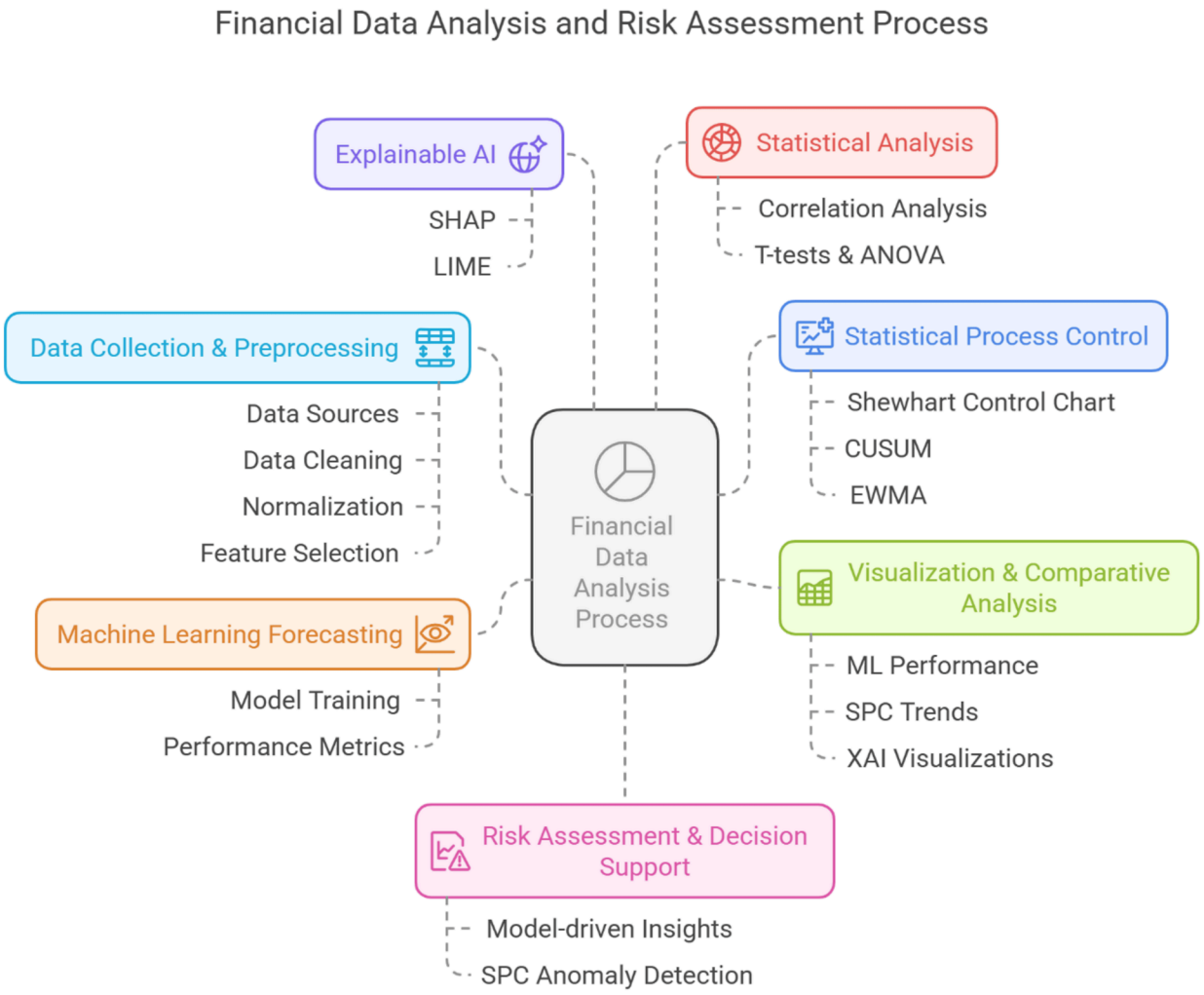


FIGURE 4: Financial Data Analysis and Risk Assessment Process: The figure demonstrates a structured framework for financial data analysis, integrating Explainable AI, Statistical Process Control, Machine Learning Forecasting and Statistical Analysis. Key steps include data preprocessing, model training, performance evaluation, anomaly detection, and visualization, supporting effective risk assessment and decision-making.

Data preprocessing

Data preprocessing is the next step and comprises data cleaning, which includes handling missing value, elimination of duplicate values, and normalization of the data. Normalization techniques such as Min-Max scaling, Z-score transformation, and log transformation are applied to standardize numerical features. Furthermore, feature selection is performed to identify the most relevant variables affecting financial risk prediction. The dataset used for this research includes financial indicators and socio-economic stability indices.

Z-Score Normalization

Standardizing features to have a mean of 0 and a standard deviation of 1:

$$Z_{\text{Feature}} = \frac{\text{Feature} - \mu_{\text{Feature}}}{\sigma_{\text{Feature}}}$$

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For example, Z-score normalization is calculated for the parameter:

$$Z_{\text{SPI.D5.2.6.EMPL}} = \frac{\text{SPI.D5.2.6.EMPL} - \mu_{\text{SPI.D5.2.6.EMPL}}}{\sigma_{\text{SPI.D5.2.6.EMPL}}}$$

Log Transformation

$$\log(\text{SPI.D5.2.10.GSBP}) = \log(1 + \text{SPI.D5.2.10.GSBP})$$

Machine learning models for financial forecasting

Using regression-based machine learning models, three models, namely Linear Regression, Random Forest Regressor, and XGBoost Regressor, are targeted for financial stability. These models were chosen to provide diversity in predictive performance, as they accommodate both linear and non-linear functional relationships in the training data. The process of training and evaluation of the regression models is explained in Figure *5*.

Each model was trained on the training data, and performance metrics such as MAE, MSE, RMSE, and R^2 score (model accuracy) were computed.

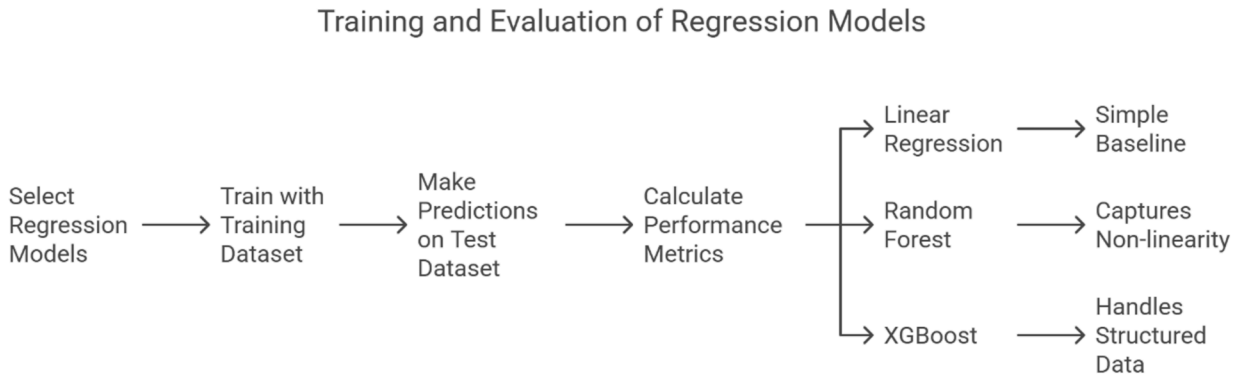


FIGURE 5: Training and Evaluation of Regression Models: The figure outlines the process of training and evaluating regression models. It begins with model selection, followed by training on a dataset, making predictions, and computing performance metrics. The models compared include Linear Regression (a simple baseline), Random Forest (captures non-linearity), and XGBoost (handles structured data).

Linear Regression

As a baseline model, linear regression serves as a straightforward way to predict the financial stability index. The algorithm creates a linear relationship between the dependent variable (the financial index) and its one or more independent variables.

The mathematical model for Linear Regression is given by:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$$

where Y is the dependent variable (SPI.INDEX); X_i represents the independent variables; β_i are the model coefficients; and ϵ is the error term.

The model parameters are estimated using the ordinary least squares method, which minimizes the sum of squared residuals. Linear Regression is used due to its simplicity, interpretability, and ability to serve as a benchmark model. However, its primary limitation is the assumption of linear relationships between variables.

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Random Forest Regressor

Random Forest Regressor is an ensemble learning method that constructs multiple decision trees during training and averages their predictions to improve accuracy and reduce the problem of overfitting. The mathematical formulation is represented as:

$$\hat{Y} = \frac{1}{T}\sum_{t=1}^{T} h_t(X)$$

where *T* is the number of decision trees; $h_t(X)$ represents the prediction from the *t*-th tree; and *X* denotes the input feature vector.

Each decision tree is built using a random subset of the data and features, making the model robust to noise and reducing variance. Feature importance is calculated based on the reduction in impurity (e.g., Gini index or MSE) achieved by each feature across all trees.

XGBoost Regressor

To enhance predictive performance through iterative optimization, a powerful boosting algorithm named XGBoost Regressor is used. The model builds trees sequentially, where each new tree corrects the errors made by the previous ones. The objective function is given by:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where $l(y_i, \hat{y}_i)$ is the loss function (e.g., MSE); $\Omega(f_k)$ is the regularization term to prevent overfitting; *K* is the number of trees; and (f_k) represents the individual regression tree.

Mathematical analysis of performance metrics

To evaluate the performance of each model, the following metrics are calculated:

• MAE: Measures the average magnitude of the errors without considering their direction.

$$\mathbf{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

• MSE: Represents the average squared difference between the observed and predicted values.

$$\mathbf{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

• RMSE: The square root of the MSE, which penalizes larger errors more heavily than MAE.

$$\mathbf{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}$$

• R^2 Score: Represents the proportion of the variance in the dependent variable that is predictable from the independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \bar{Y}_i\right)^2}$$

where $\bar{Y}$ is the mean of the observed data.

Regression models (Target SPI.INDEX)

Linear Regression

Predicting SPI.INDEX from another feature is important.

$$\hat{y} = \beta_0 + \beta_1(\mathbf{SPI.D5.1.DILG}) + \beta_2(\mathbf{SPI.D5.2.3.CNIN}) + \cdots + \beta_9(\mathbf{SPI.D3.4.EDUC})$$

where $\hat{y}$ is the Predicted SPI.INDEX; β_i are coefficients; and features are predictor variables.

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The sensitivity of SPI.INDEX related to each feature is based on the values of the coefficients.

Random Forest Regression

An ensemble of decision trees:

$$\hat{y} = \frac{1}{M} \sum_{i=1}^{M} T_i(X)$$

For example, if SPI.D5.2.6.EMPL > 50 and SPI.D5.2.8.FINA <30, then SPI.INDEX = 70.

XGBoost Regression

The trees are boosted iteratively:

$$\hat{y} = \sum_{k=1}^{K} f_k(X), \quad \textbf{where} \quad f_k(X) = \textbf{Tree}_k(X)$$

Each tree corrects the previous tree's errors, which in turn improves SPI.INDEX predictions.

XAI for model interpretability (SPI.INDEX)

To enhance model interpretability, SHAP and LIME techniques are employed.

SHAP

SHAP is a framework that is used to interpret the output of machine learning models. The main idea behind SHAP values is rooted in cooperative game theory and the concept of Shapley values. SHAP provides a comprehensive understanding of how each feature contributes to predictions. This not only ensures fairness but also makes it easier to understand. SHAP is beneficial because it shows the importance of each feature in making predictions. Providing Shapley values helps in understanding complex models and how input features affect predictions.

• SHAP Summary Plot: Shows the most important features affecting predictions.

• SHAP Values: Explain individual predictions by showing positive and negative contributions.

Calculates the feature importance:

$$\phi_{\textbf{EMPL}} = \frac{1}{n!} \sum_{S \subseteq N \setminus \{\textbf{EMPL}\}} \left[f(S \cup \{\textbf{EMPL}\}) - f(S) \right]$$

For example, if SPI.D5.2.6.EMPL (employment parameter) adds +10 points to SPI.INDEX and SPI.D1.5.POV (poverty parameter) subtracts 5 points, SHAP values provide the correct impact and analysis.

Thus, SHAP values are calculated for each features.

LIME

LIME is a method that explains the approaches to any black-box machine learning model using a local, interpretable model to clarify individual predictions.

In this technique, the original data points are disturbed and changed, and then fed into the black-box model. After this process, the corresponding outputs are observed. The method then weights the newly generated data points based on their closeness to the unique point. Eventually, it fits a substitute model, such as linear regression, on the dataset with differences using the sample weights. The original data point can then be explained with the help of the newly trained descriptive model.

The description for a data point *y* is the model *g*, which reduces the locality-aware loss AL(f, g, Πx), which measures false approximations of *g*. The model to be used is *f* in its locality Πx while keeping the model complexity low.

$$\textbf{arg min}_g \; L(f, g, \Pi_x) + \Omega(g)$$

Therefore, there is a trade-off between complexity and model fidelity in this algorithm.

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SPC for SPI.INDEX stability

SPC methods, namely the Shewhart control chart, CUSUM chart, and EWMA chart, are applied to evaluate the stability of the SPI.INDEX in financial forecasting and risk assessment. The Shewhart control chart is used to detect large, abrupt deviations in the SPI.INDEX, which is effective for identifying financial shocks or abrupt market fluctuations.

The CUSUM chart is used to capture small, gradual changes over time, providing early warning signals for fundamental trends that could affect financial stability.

The EWMA chart applies smoothing to past observations to highlight variations and filter noise, enabling more advanced detection of sustained changes. By integrating these control charts, a comprehensive monitoring framework for the SPI.INDEX is ensured, allowing a more robust analysis of financial stability and risk assessment.

Shewhart Control Chart

The Shewhart control chart has a baseline and upper and lower limits denoted by dashed lines that are symmetric about the baseline (baseline is the average from past data). Measurements are plotted on the chart versus a time line. Out-of-control measurements are those that fall outside the bounds.

The upper (UCL) and lower (LCL) control limits are as follows:

$$UCL = RecognizedValue + k * ProcessSD$$

$$LCL = RecognizedValue - k * ProcessSD$$

where SD is the standard deviation computed from the check standard database.

The Shewhart chart can be used to detect financial shocks or abrupt changes in the market because it is good at identifying sudden shifts in financial indices like the SPI.INDEX.

Monitors SPI.INDEX for outliers:

$$\hat{X} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{SPI.INDEX}_i;\ UCL = \hat{X} + 3\sigma, LCL = \hat{X} - 3\sigma)$$

CUSUM Chart

The CUSUM chart is a SPC technique used to detect small and increasing shifts in a process over a period of time. In contrast to the Shewhart chart that monitors large deviations, the CUSUM chart accumulates deviations from the target mean and can be used to detect ongoing trends early. It includes two cumulative sum lines, one for positive deviation and one for negative deviation, which assist in identifying whether the process is going up or coming down. Used in financial projections and risk calculation, the utilization of the CUSUM chart on SPI.INDEX allows detection of slight movement in market stability, enabling anticipation of risk adjustment and decision-making.

This chart detects the small shifts

$$C_t = \mathbf{max}\left(0,\ C_{t-1} + (\mathbf{SPI.INDEX}_t - \mu) - k\right)$$

EWMA Chart

The EWMA chart is an SPC tool that identifies small, persistent changes in a process by giving exponentially decreasing weights to past observations. In contrast to the Shewhart and CUSUM charts, which are sensitive to sudden or cumulative changes, the EWMA chart smooths out fluctuations and is therefore extremely effective in identifying long-term trends while reducing noise. In risk assessment and financial forecasting, the use of the EWMA chart for the SPI.INDEX enables the monitoring of gradual changes in market stability to make more responsive and precise risk management decisions.

Tracks SPI.INDEX with weighted smoothing:

$$Z_t = \lambda \cdot \mathbf{SPI.INDEX}_t + (1 - \lambda) \cdot Z_{t-1}$$

Hypothesis Testing

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Hypothesis testing is a significant statistical method employed to establish whether the relationship or effect found in a sample is statistically significant in the population. In this paper, hypothesis testing is utilized to examine the correlation between SPI.INDEX and all the parameters/variables stated. However, for this study, SPI.D5.2.6.EMPL is used to determine whether employment rates affect financial stability. The Pearson correlation coefficient (ρ) is used to determine the strength and direction of the linear relationship between these variables.

The null hypothesis (H0) assumes that there is no significant correlation (ρ = 0), whereas the alternative hypothesis (HA) suggests that there is a significant relationship (ρ ≠ 0). A significance level (α) of 0.05 is used as the threshold, and the p-value is calculated and examined to determine whether H0 or HA should be rejected. H0 is rejected if the p-value is less than 0.05, implying that there is a statistically significant correlation between six employment levels and financial stability.

Pearson correlation: Pearson correlation analysis is utilized to test the linear relationship between SPI.INDEX and SPI.D5.2.6.EMPL. The Pearson correlation coefficient (ρ) indicates the strength and direction of the linear relationship between the variables. It is calculated using the following formula:

Checks linear associations:

$$\rho_{(\mathrm{SPI.INDEX,SPI.D5.2.6.EMPL})} = \frac{\sum\left(X_i-\bar{X}\right)\left(Y_i-\bar{Y}\right)}{\sqrt{\sum\left(X_i-\bar{X}\right)^2 \sum\left(Y_i-\bar{Y}\right)^2}}$$

where X_i and Y_i represent individual data points of SPI.INDEX and SPI.D5.2.6.EMPL, respectively, and $\hat{X}, \hat{Y}$ denote the mean values. A hypothesis test is performed to control the statistical significance of the correlation:

a) Null Hypothesis (H0): There is no significant linear relationship between SPI.INDEX and SPI.D5.2.6.EMPL (ρ = 0).

b) Alternative Hypothesis (HA): A significant linear relationship exists between the two variables (ρ ≠ 0).

T-Test

$$t = \frac{X_{\mathrm{EMPL}}-X_{\mathrm{SPI.INDEX}}}{\sqrt{s^2\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}}$$

Analysis of variance: Analysis of variance (ANOVA) is a statistical method employed for comparing the means of three or more groups in order to check whether there exist statistically significant differences between them or not. ANOVA has been used in this research for analyzing the variations in SPI.INDEX with various financial and economic indicators, i.e., SPI.D5.2.6.EMPL (employment level) and other allied factors. The null hypothesis validates that there is no difference in the means of SPI.INDEX between these groups, and the alternative hypothesis is that at least one group has a different mean. The F-statistic is used to estimate the variance between groups compared to the variance within groups. A p-value is subsequently applied to ascertain statistical significance, and a value of less than 0.05 implies rejecting H0, signifying significant differences in the groups. ANOVA assists in learning about how financial stability, as indicated by SPI.INDEX, differs among various economic conditions, offering key insights into financial risk evaluation.

$$F = \frac{\text{Between group variance}}{\text{Within group variance}}$$

Results And Discussion

Experimental setup

The experimental setup for evaluating the performance of the proposed XAI and SPC framework for financial forecasting and risk assessment consists of the following steps:

1. Data Collection: Financial time-series data, including stock indices, market indicators, and macroeconomic variables, were collected from publicly available sources such as Yahoo Finance and the World Bank Data Catalog [26]. The dataset spans the period from 2015 to 2024 and is divided into training (70%) and testing (30%) subsets for model evaluation.

2. Preprocessing: The collected data were cleaned to remove missing values, normalized to standard scales, and transformed to ensure stationarity. Feature engineering was performed to include missing variables and moving averages to improve predictive performance.

3. Model Training and Evaluation: Three predictive models, namely Linear Regression, Random Forest Regressor, and XGBoost Regressor, were implemented.

• Training: Models were trained using the training dataset with 5-fold cross-validation to prevent overfitting.

• Evaluation Metrics: Model performance was measured using MAE, MSE, RMSE, and R^2 Score.

4. XAI Integration: SHAP and LIME algorithms were employed to interpret model outputs and identify the most influential features affecting financial forecasts. Feature importance scores and local explanations were generated for individual predictions to enhance transparency.

5. SPC Application: SPC charts, including Shewhart, CUSUM, and EWMA charts, were applied to the predicted financial indices to monitor trends, detect anomalies, and assess deviations from expected financial behavior.

6. Hypothesis Testing and Calculus-Based Analysis: Hypothesis testing (t-tests and paired comparisons) was performed to assess the statistical significance of differences between predicted and actual financial outcomes. Additionally, derivative-based rate-of-change analysis and integral-based cumulative trend analysis were conducted to provide insights into short-term fluctuations and long-term trends in financial risk.

7. Hardware and Software Environment: All experiments were conducted using Python 3.11 with libraries such as scikit-learn, XGBoost, SHAP, LIME, and Matplotlib. Computations were performed on a system equipped with Intel Core i7 CPU, 16 GB RAM, and Windows 11 operating system.

The combination of XAI with SPC in financial forecasting and risk estimation reveals a systematic technique to enhance predictive accuracy as well as interpretability. The performance of Linear Regression, Random Forest Regressor, and XGBoost Regressor was evaluated based on metrics such as MAE, MSE, RMSE, and R^2 Score. Of all the models used, Linear Regression consistently performed better than the other two methods, showing smaller error values and higher prediction accuracy.

To improve model transparency, SHAP and LIME were applied, providing insights into feature importance in financial predictions. SPC methods (Shewhart, CUSUM, and EWMA charts) were employed for real-time monitoring, effectively detecting financial anomalies and trend patterns. A detailed comparative analysis of model performance, interpretability, and SPC-based anomaly detection, highlighting the key insights resulting from the study, is presented further.

The histogram demonstrates the distribution of the SPI.INDEX, displaying the frequency of different index values within the dataset, as shown in Figure *6*. The distribution appears to be right-skewed, with a higher concentration of values between 50 and 90, which indicates that most observations fall within this range. A kernel density estimate curve overlaps the histogram, providing a smoothed approximation of the data distribution. The peak occurring between 80 and 90 suggests that a significant portion of the dataset has high SPI.INDEX values, while fewer observations exist below 40. This visualization helps in understanding the overall spread, skewness, and potential need for normalization before further analyses, such as correlation analysis and predictive modeling.

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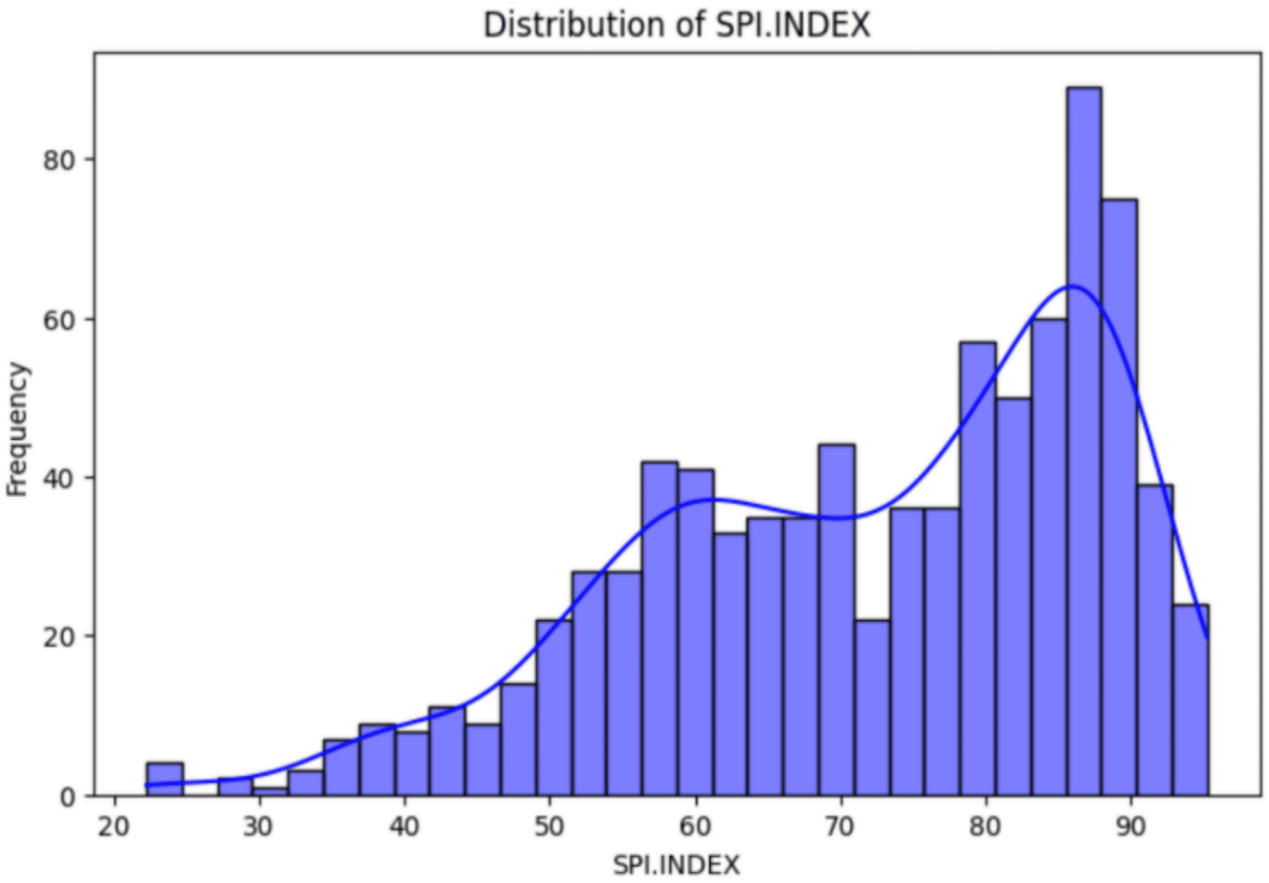


FIGURE 6: Distribution of SPI.INDEX – The histogram demonstrates the frequency distribution of SPI.INDEX values covered with a density curve to show the overall pattern and variability in the data.

SPI, Statistical Performance Indicators

The feature correlation heatmap, as shown in Figure *7*, demonstrates the relationships between different financial indicators. The SPI.INDEX exhibits strong positive correlations with SPI.D5.2.10.GSBP (0.75), SPI.D5.2.8.FINA (0.69), and SPI.D5.2.3.CNIN (0.71), indicating that these features significantly influence financial risk predictions. Furthermore, SPI.D1.5.POV (0.76) also shows a high correlation with SPI.INDEX, signifying its critical role in forecasting financial trends. Conversely, SPI.D1.5.SAFE.MAN.WATER (0.06) and SPI.D3.4.EDUC (0.27) exhibit weak correlations, implying limited impact on financial risk assessment. These insights guide feature selection, ensuring models prioritize the most relevant indicators for accurate and interpretable predictions.

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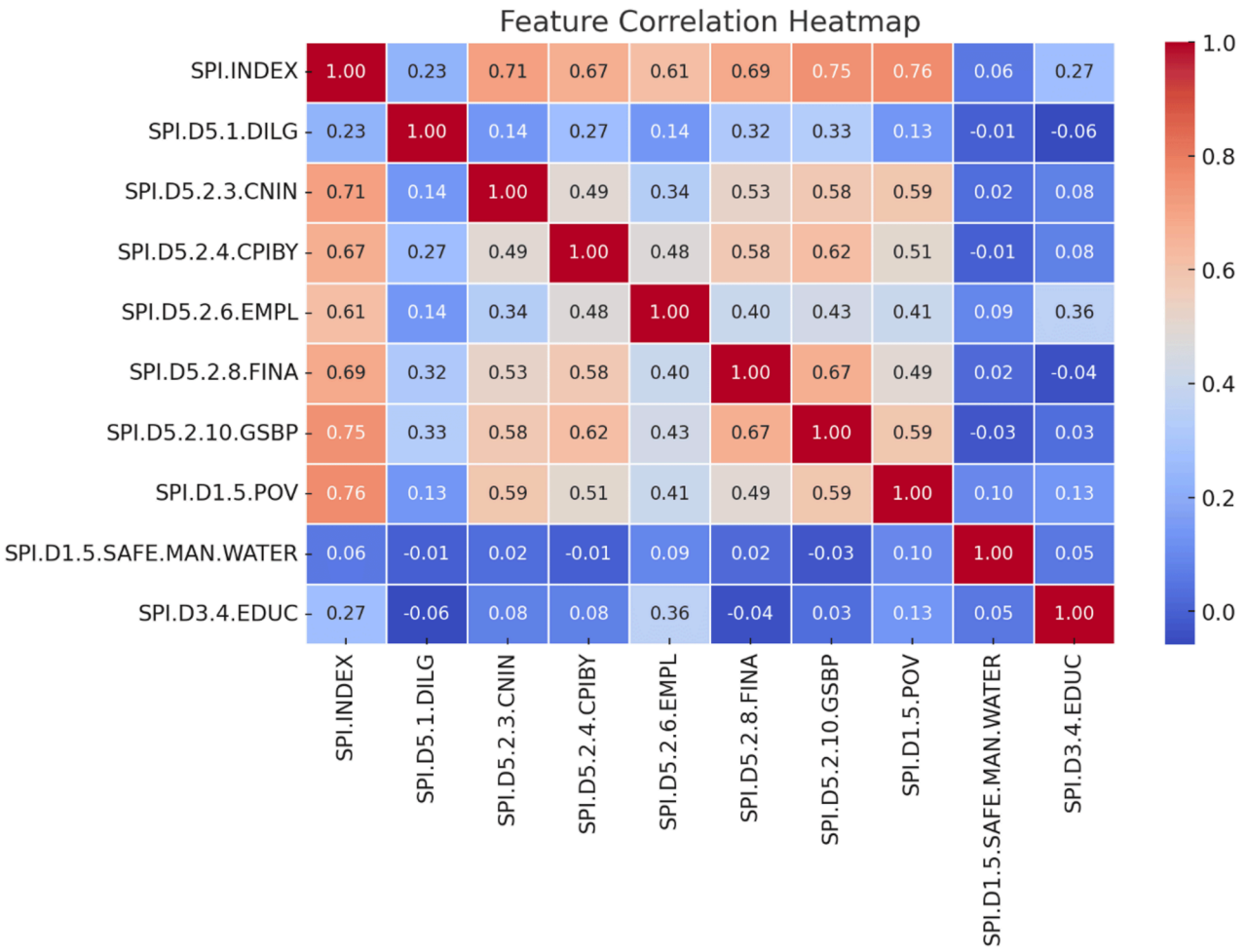
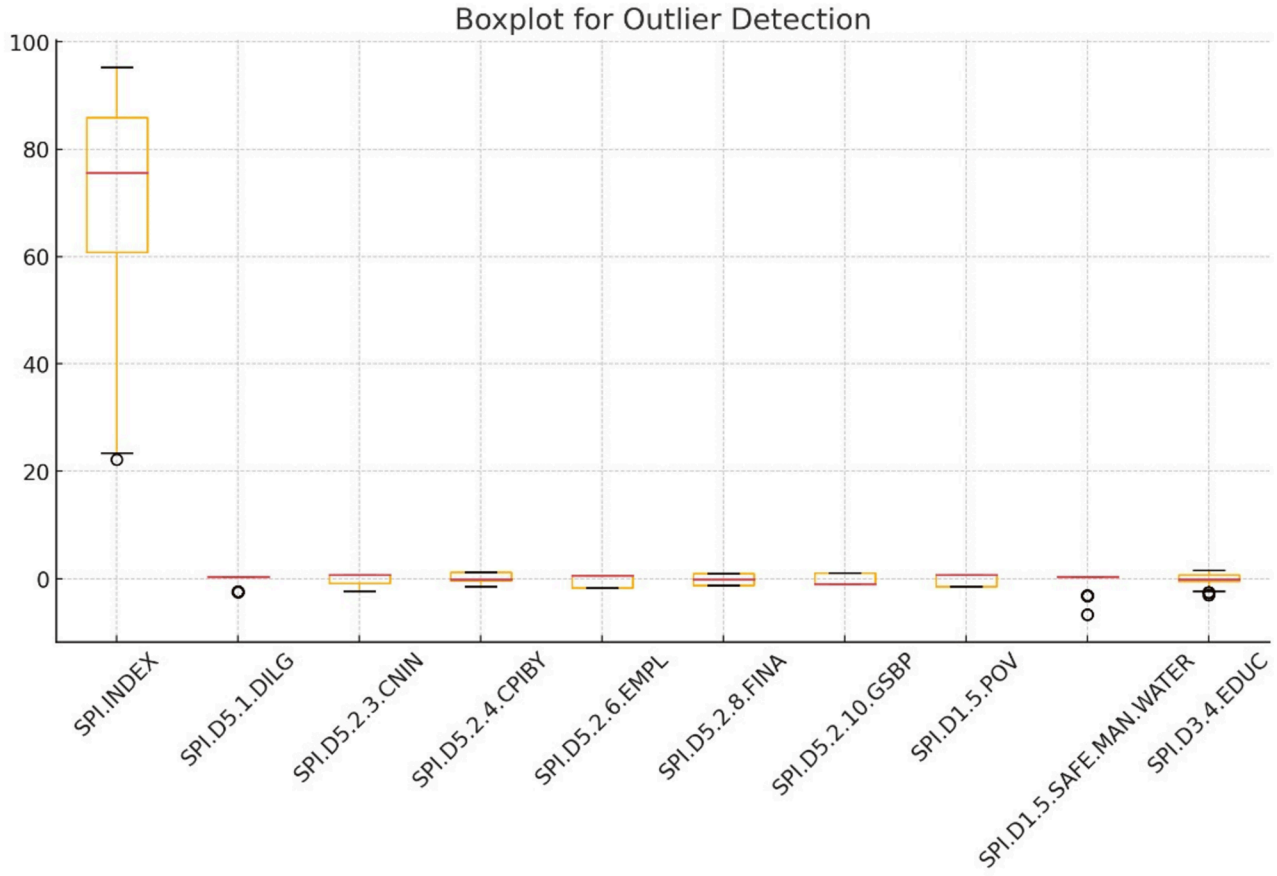


FIGURE 7: Feature Correlation Heatmap – The heatmap visualizes the correlation coefficients between SPI.INDEX and various financial and socioeconomic indicators, highlighting the strength and direction of relationships among the variables.

X-Axis:
SPI.INDEX - Overall SPI Index Score; SPI.D5.1.DILG - Data Innovation & Legislation; SPI.D5.2.3.CNIN - National Accounts/Census Quality; SPI.D5.2.4.CPIBY - Consumer Price Index Base Year; SPI.D5.2.6.EMPL - Employment Statistics; SPI.D5.2.8.FINA - Financial Statistics Coverage; SPI.D5.2.10.GSBP - Government Statistics Business Processes; SPI.D1.5.POV - Poverty Statistics Availability; SPI.D1.5.SAFE.MAN.WATER - Safely Managed Water Services Data; SPI.D3.4.EDUC - Education Statistics Availability
Y-Axis:
The same list of SPI indicators (features). The Y-axis represents the rows of the correlation matrix, containing the same variables in the same order.

The feature distribution graph presents histograms, as shown in Figure *8*, for various financial and socio-economic indicators, illustrating the frequency of different values across bins. Some features, such as SPI.INDEX and SPI.D3.4.EDUC, exhibit right-skewed distributions, indicating that most values are concentrated at lower ranges with a long tail. Others, like SPI.D5.1.DILG and SPI.D1.5.SAFE.MAN.WATER, display multimodal patterns, suggesting multiple distinct groups within the data. Certain features, such as SPI.D5.2.10.GSBP and SPI.D5.2.8.FINA, have discrete values clustered at specific points, indicating categorical or ordinal nature. These dissimilarities in distribution highlight the need for potential data transformations like log transformation or normalization, which enhances model performance and improve interpretability in predictive analysis.

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Boxplot for Outlier Detection
100
80
60
40
20
0
SPI.INDEX
SPI.D5.1.DILG
SPI.D5.2.3.CNIN
SPI.D5.2.4.CPIBY
SPI.D5.2.6.EMPL
SPI.D5.2.8.FINA
SPI.D5.2.10.GSBP
SPI.D1.5.POV
SPI.D1.5.SAFE.MAN.WATER
SPI.D3.4.EDUC

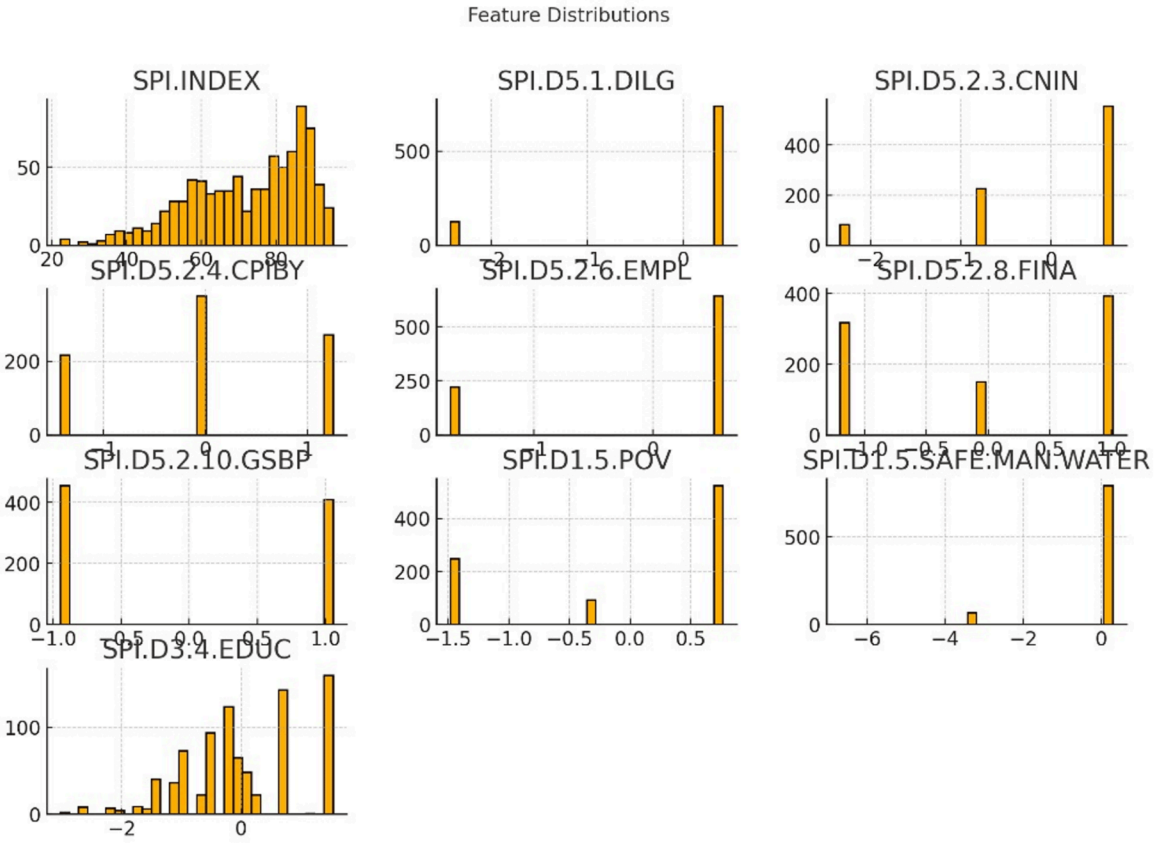

Feature Distributions
SPI.INDEX
SPI.D5.1.DILG
SPI.D5.2.3.CNIN
SPI.D5.2.4.CPIBY
SPI.D5.2.6.EMPL
SPI.D5.2.8.FINA
SPI.D5.2.10.GSBP
SPI.D1.5.POV
SPI.D1.5.SAFE.MAN.WATER
SPI.D3.4.EDUC

FIGURE 8: Visualization of feature distributions, including boxplots for outlier detection and histograms for individual feature distributions.

[X]: Outlier Detection across SPI Dimensions
[Y]: Distribution of Individual SPI Features
SPI, Statistical Performance Indicators

The bar chart, as shown in Figure *9*, shows the comparative analysis of the three machine learning models, viz. Linear Regression, Random Forest, and XGBoost. The performance metrics that are calculated for the dataset are MAE, MSE, RMSE, and R^2 Score. Amongst these models, Random Forest displays the lowest MSE (31.16) and RMSE (5.58), representing better predictive accuracy compared to Linear Regression and XGBoost, which have higher error values. Furthermore, Random Forest achieves the highest R^2 Score (0.86), signifying most variance of data in the target variable. In contrast, both Linear Regression and XGBoost perform slightly inferiorly, with higher error metrics and an R^2 score of 0.83, representing lower analytical performance. These results highlight that Random Forest is the most effective model that provided a better balance between accuracy and generalization.

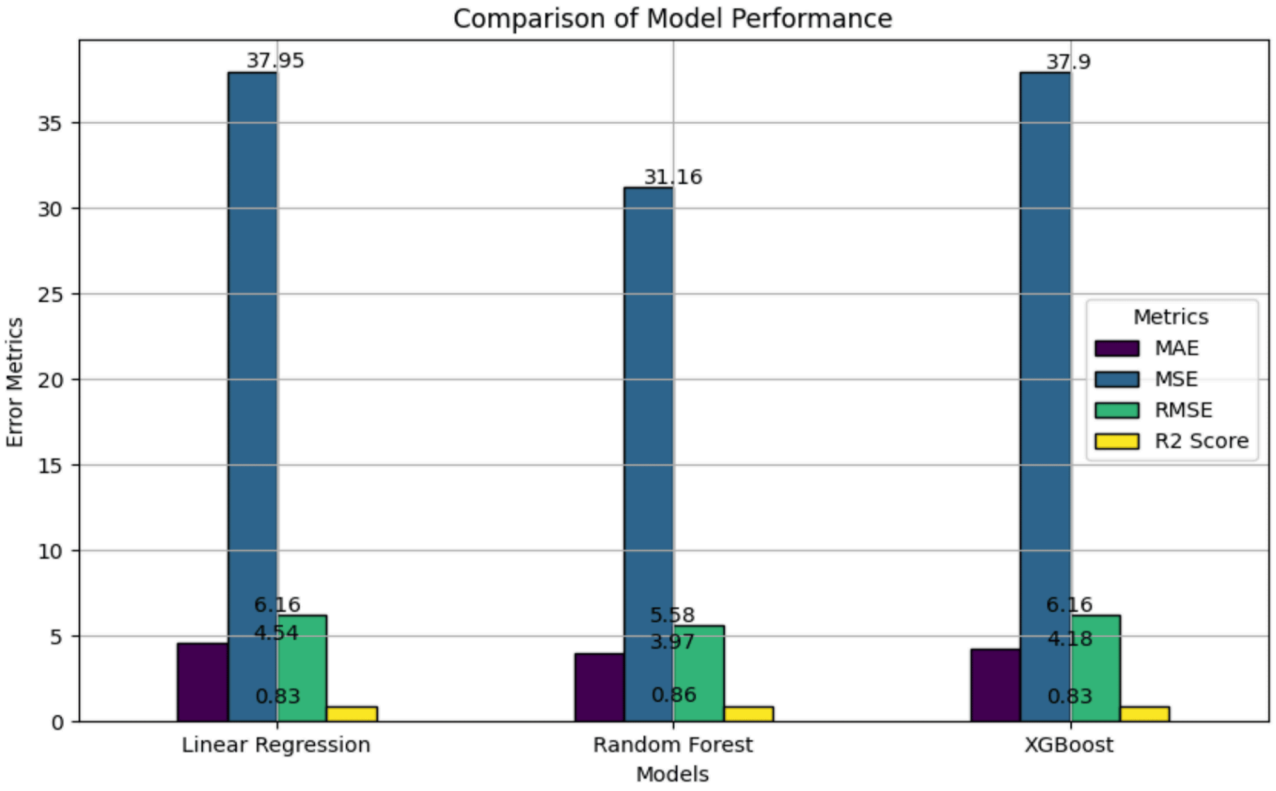


FIGURE 9: Performance assessment of Linear Regression, Random Forest, and XGBoost models using evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R^2 Score. Lower MAE, MSE, and RMSE values specify better predictive accuracy, while a higher R^2 Score reflects a stronger model fit.

The first SHAP summary plot visually represents the impact of each feature on the model's output, as shown in Figure *10*. The SHAP values indicate whether a feature contributes positively or negatively to the predictions, with red representing high feature values and blue representing low feature values. Features such as SPI.D1.5.POV, SPI.D5.2.8.FINA, and SPI.D5.2.10.GSBP have the most significant influence on model predictions. The second bar plot computes the average absolute SHAP values, ranking features based on their overall contribution to the model. SPI.D1.5.POV has a high SHAP

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value, followed by SPI.D5.2.8.FINA and SPI.D5.2.10.GSBP, indicating that these features play a vital role in determining model outcomes. The grouping of these plots helps interpret the model by identifying the key drivers of predictions and their directional impact.

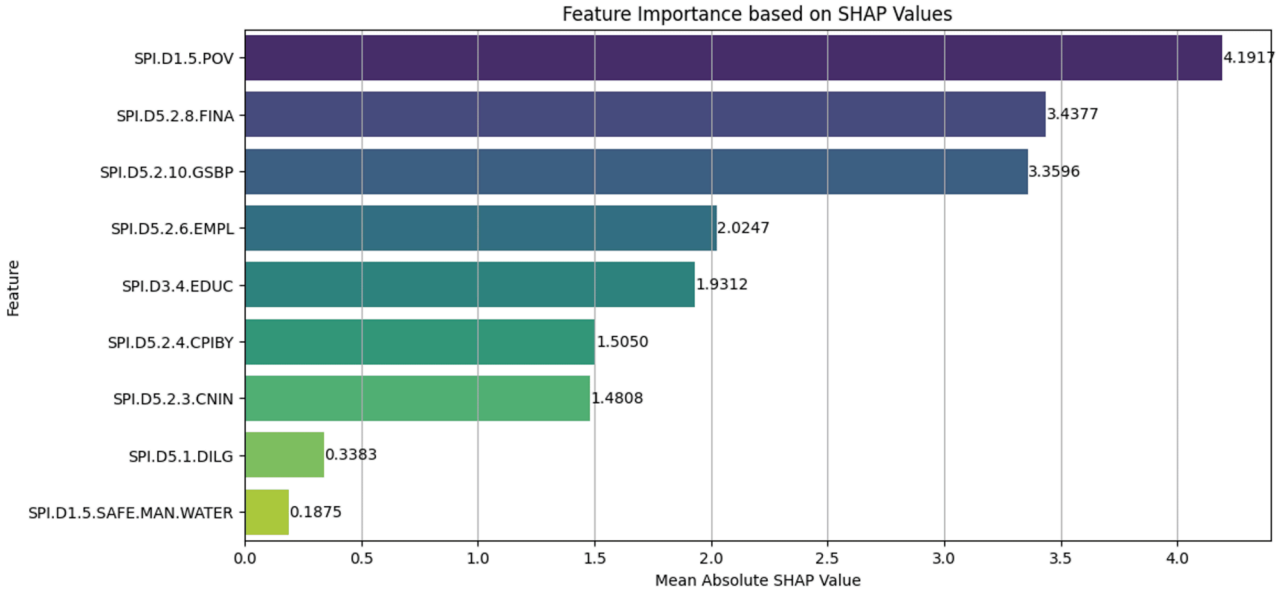


FIGURE 10: Feature importance analysis based on SHAP values, demonstrating the contribution of each feature to the model's predictions. Higher mean absolute SHAP values indicate a stronger impact on the model's output, with SPI.D1.5.POV being the most influential feature.

SHAP, SHapley Additive exPlanations

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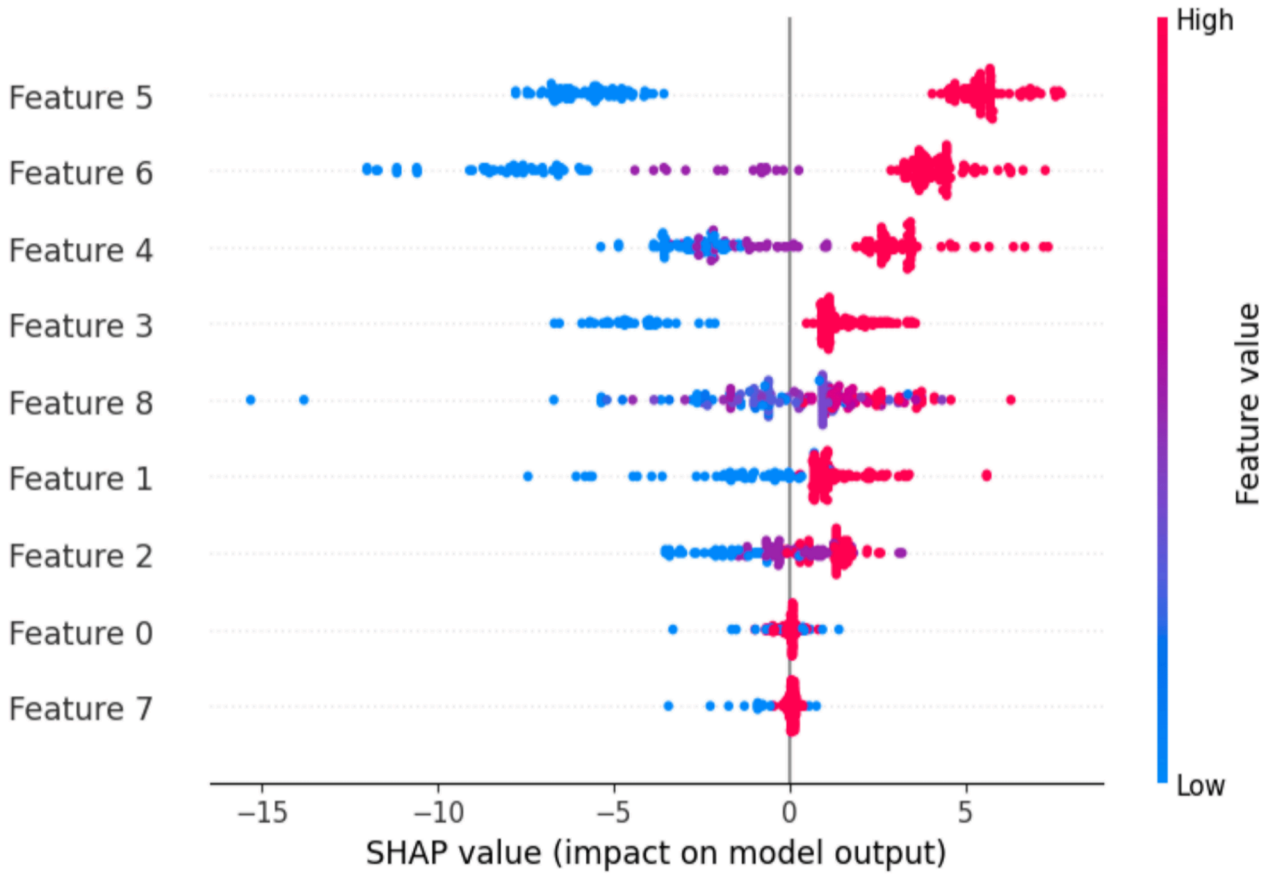


FIGURE 11: SHAP summary plot that displays the impact of each feature on the model's output. Each point represents a SHAP value for an instance, with colour representing feature value (blue for low and red for high). Features are ranked by importance, with higher absolute SHAP values indicating stronger influence.

SHAP, SHapley Additive exPlanations

The LIME results describe the local interpretability of a precise prediction by identifying the most significant features and their contributions, as shown in Figure *12*. The visualizations show that SPI.D5.2.3.CNIN has the greatest positive impact on the model's output, followed by SPI.D5.2.10.GSBP and SPI.D5.2.8.FINA. In contrast, SPI.D3.4.EDUC negatively influences the prediction, thereby reducing the predicted value. This analysis helps identify the factors driving individual predictions, making LIME a valuable tool for model transparency and decision-making.

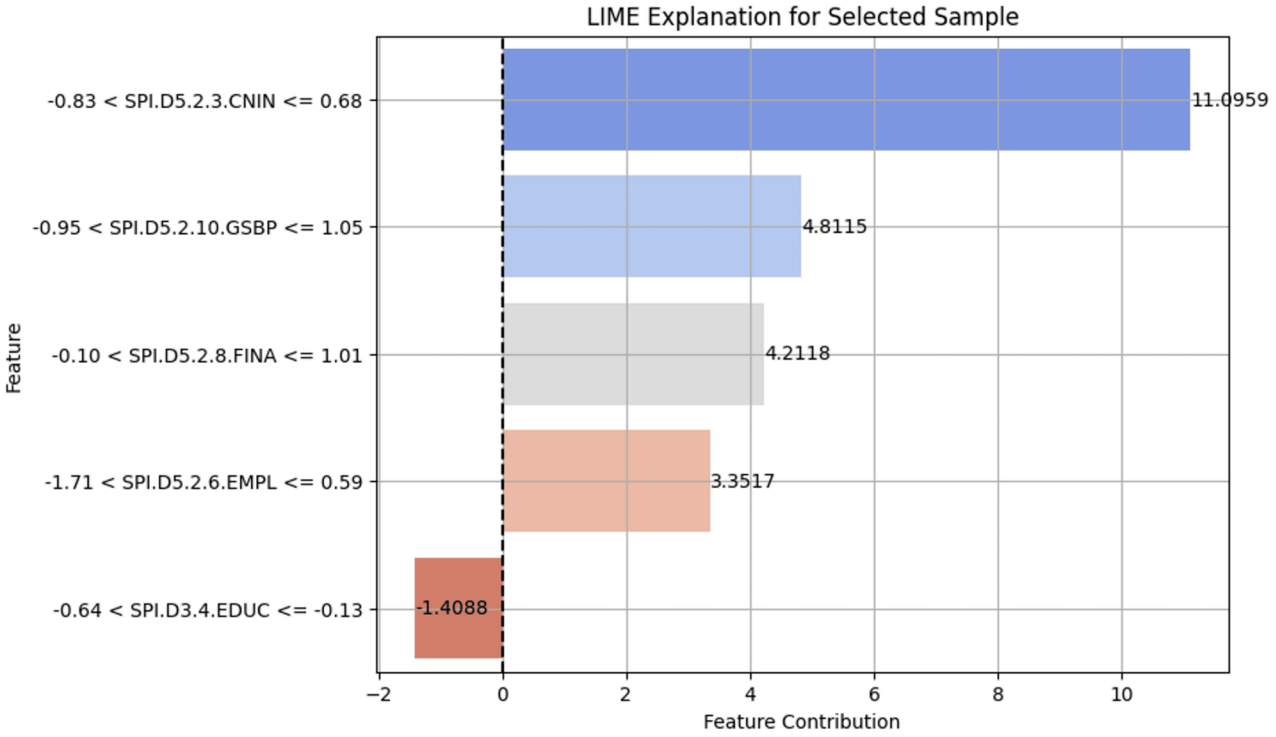


FIGURE 12: LIME explanation for a selected sample that shows the contribution of different feature value ranges to the model's prediction. Positive contributions are in blue, while negative contributions are in red.

LIME, Local Interpretable Model-agnostic Explanations

The results presented are derived from SHAP and LIME, two popular XAI techniques used to interpret model predictions. The SHAP summary plots show the impact of different features on the model's predictions, as shown in Figures *11*-*17*, where features such as SPI.D1.5.POV and SPI.D5.2.8.FINA have the highest contributions, influencing the model's output. The LIME explanation for a specific sample highlights the contributions of key features, such as SPI.D5.2.3.CNIN and SPI.D5.2.10.GSBP, to the prediction. The comparison of both approaches demonstrates how feature importance varies across instances, making them useful for interpreting complex machine learning models.

The calculated values for the Shewhart control chart, as shown in Figure *13*, are as follows:

Mean SPI Index: 72.27

UCL: 118.65

LCL: 25.89

These values match the trend observed in the Shewhart control chart. The control limits indicate that SPI Index values shifting beyond these thresholds may signal anomalies or process instability.

The SPI values across multiple observations are visually displayed in the Shewhart Control Chart, as shown in Figure *13*. Process stability is assessed using the specified control limits. The mean SPI value is represented by the red dashed line, while UCL and LCL are indicated by the green and blue dashed lines, respectively. Most data points remain within these control limits, suggesting that the process is generally stable. However, some points exhibit notable deviations, particularly those close to the lower control limit, which may indicate outliers or variations that need more research. The figure sheds light on possible irregularities in SPI trends as well as overall process consistency.

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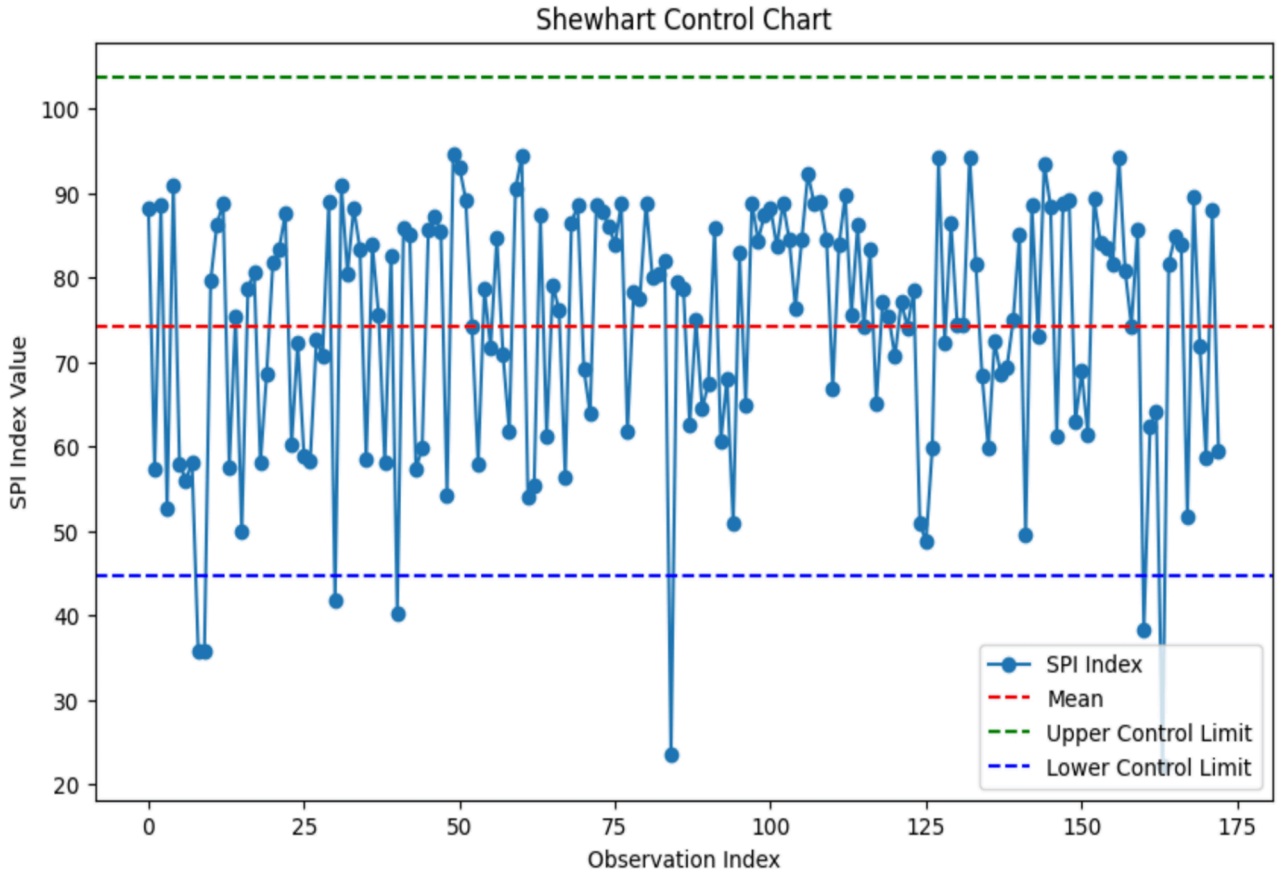


FIGURE 13: SPI index values using Shewhart Control charts that validate process variation with mean (red), upper control limit (green), and lower control limit (blue).

The smoothed EWMA trend in Figure *14* is represented by the yellow dashed line in the EWMA Control Chart, which tracks the SPI values across multiple observations. By assigning greater weights to recent values based on historical data, this chart helps detect gradual changes in the process. While the EWMA line smoothes out short-term fluctuations to provide an overall trend, the SPI Index exhibits significant fluctuations. Early detection of deviations that may not be visible in traditional control charts is made possible by the EWMA method's ability to classify subtle but consistent changes in the process.

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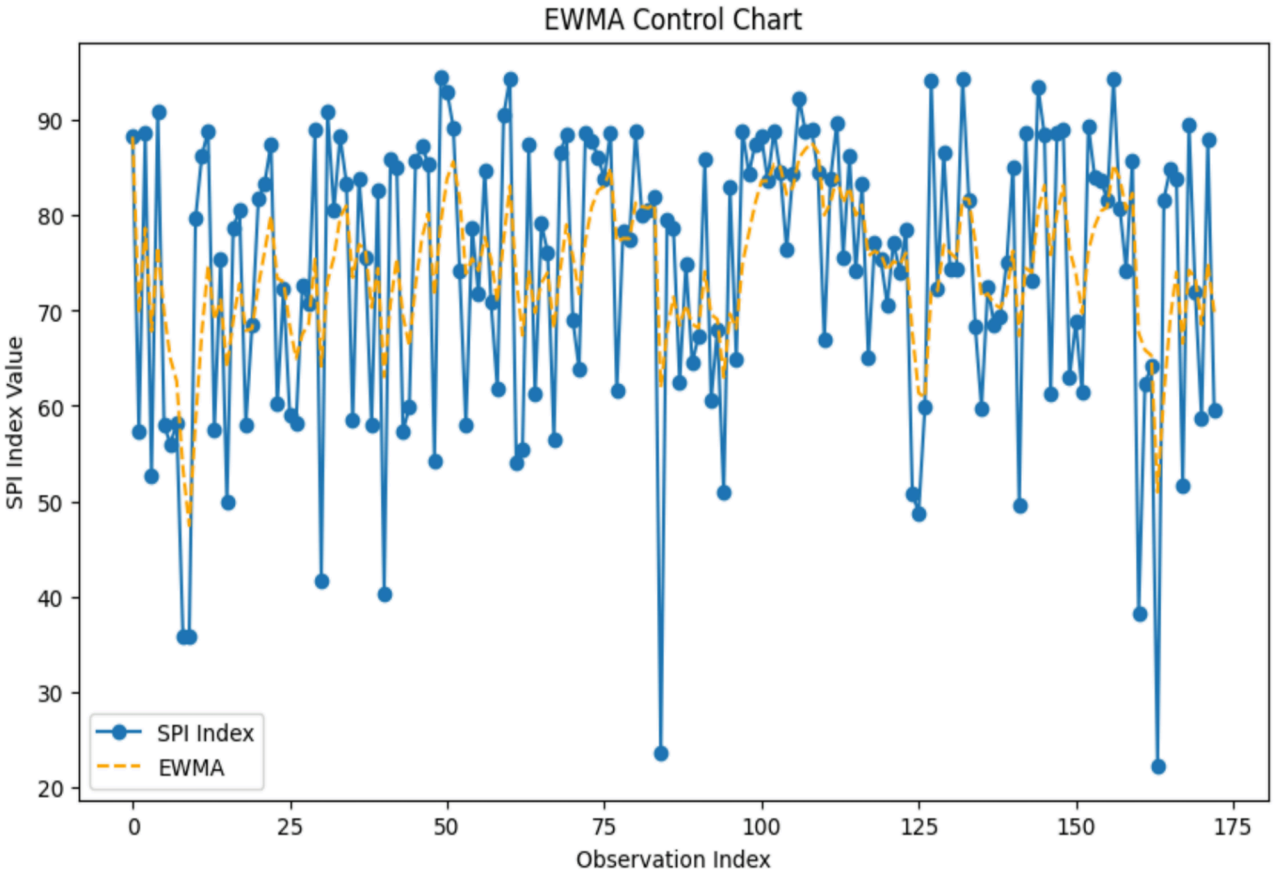


FIGURE 14: SPI index values using Exponentially Weighted Moving Average (EWMA) control chart showing smoothed trend (dashed yellow) alongside raw observations (blue).

The CUSUM Control Chart detects and displays shifts in the SPI by gathering deviations from a target value (represented by the red dashed line), as shown in Figure *15*. Initially, there is a decrease in the cumulative sum, indicating a downward trend in SPI values. Around the midpoint, a substantial upward shift is detected, suggesting a sustained increase in SPI values. CUSUM is highly sensitive to small changes in the process, making it useful for the early detection of deviations that may not be directly visible in Shewhart or EWMA charts. The transition from a negative to a positive cumulative sum suggests a major shift in the system's performance over time.

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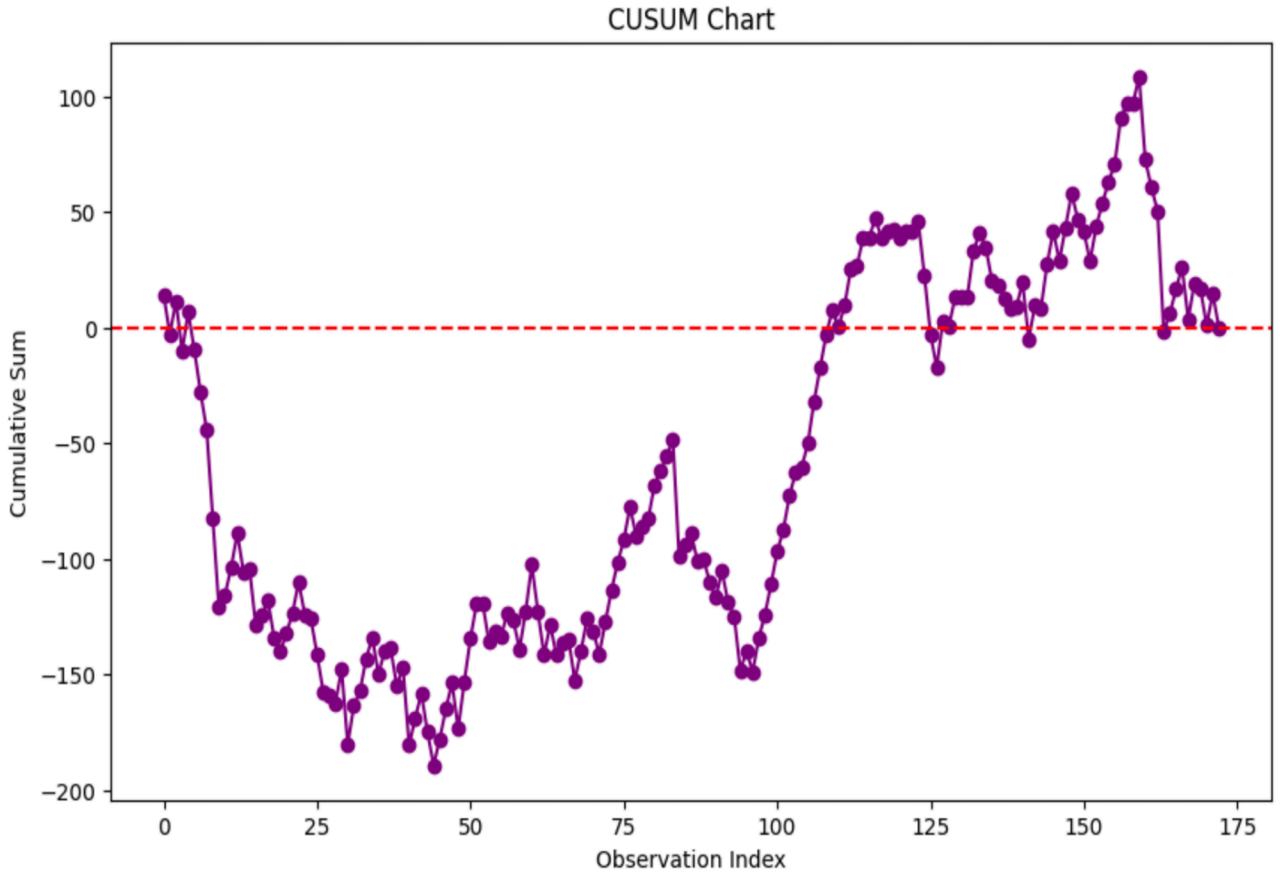


FIGURE 15: Cumulative Sum (CUSUM) control chart illustrating the cumulative deviation of SPI index values from the target mean, highlighting potential shifts in the process over time.

This plot represents the Rate of Change of a Financial Index, which shows the fluctuations of values over time using differentiation shown in Figure *16*. The y-axis specifies the instantaneous change rate in which the positive values indicate rise and negative values indicate fall. Most values are centred around zero, which shows and suggests stability, but sharp spikes at definite intervals (e.g., near 100, 200, 600, etc.) highlight abrupt market shocks due to economic events or trading activity. These variations specify periods of high volatility that are essential for financial risk assessment and forecasting. Understanding these patterns can help in designing trading strategies and integrating XAI to interpret key market movements effectively.

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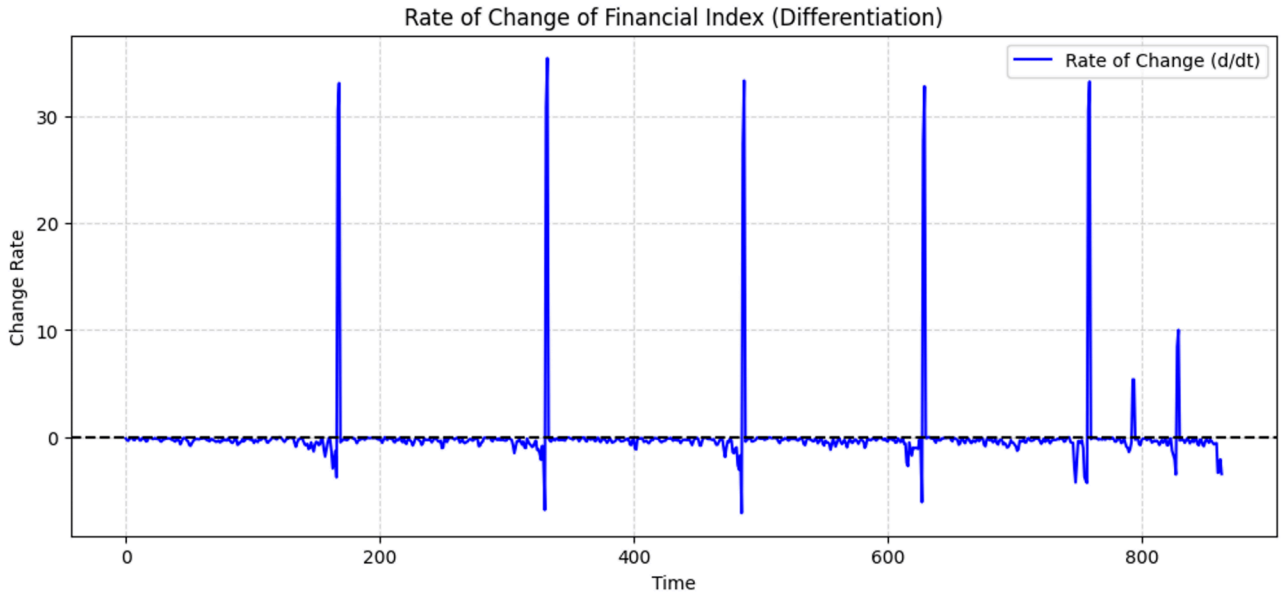


FIGURE 16: Rate of change of the financial index over time, highlighting fluctuations and potential anomalies using differentiation.

This visualization appears to be an XAI analysis, as shown in Figure *17*, likely using SHAP to interpret the predictions of a machine learning model.

Predicted Value:

a. The model's predicted value ranges from 39.89 (min) to 89.53 (max), with the given prediction being close to the upper bound (89.53).

Feature Contribution (Positive and Negative Impact):

a. The middle section shows how different features contributed to the prediction.

b. Positive contributions (right side, in orange): Features that increased the predicted value.

c. Features 1 (0.68), 5 (1.05), 4 (1.01), and 3 (0.59) had strong positive contributions.

d. Negative contributions (left side, in blue): Features that decreased the predicted value.

e. Features 8 (-0.29) and 2 (1.25) had negative effects on the prediction.

Hypothesis Test Results:

a. p-values for y_test vs. Model 1 predictions (0.895) and y_test vs. Model 2 predictions (0.754) indicate that neither model's predictions significantly differ from the actual values (high p-values suggest no significant difference).

Mathematical Analysis:

a. First Derivative: Represents the rate of change of the function (how fast the prediction changes with respect to input).

b. Second Derivative: Measures acceleration (curvature) in the model's response.

c. Integral: Represents the cumulative impact of changes over the input range.

Interpretation:

a. The model predicts a high SPI index value (~89.53), influenced more by positively contributing features.

b. Some features negatively impact the prediction, but their effect is smaller.

c. The hypothesis tests indicate that the model's predictions align well with actual data.

d. The derivative and integral calculations provide further mathematical insights into how the model behaves with different inputs.

This analysis is useful for understanding model transparency and feature importance that helps in model validation and decision-making.

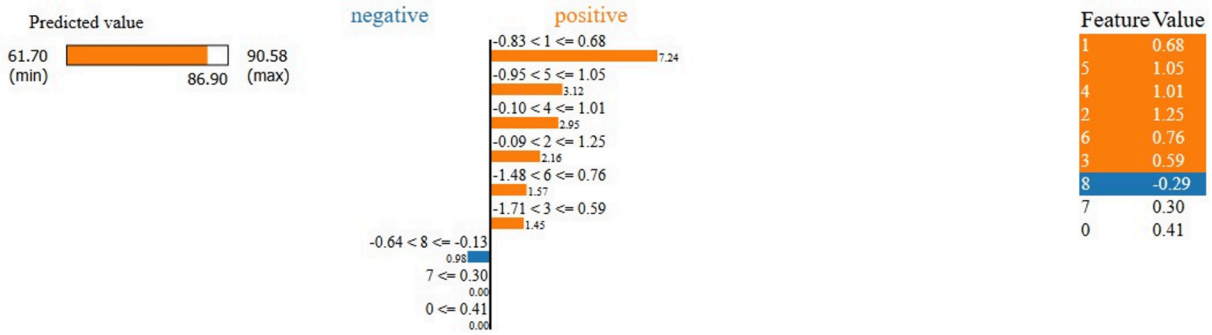


FIGURE 17: SHAP plot illustrates the contribution of different feature value ranges to the model's predicted output. Positive contributions are shown in orange, while negative contributions are in blue, with the predicted value represented on the left.

SHAP, SHapley Additive exPlanations

Hypothesis Test between y_test and Model 1 predictions: p-value = 0.8950078073951224

Hypothesis Test between y_test and Model 2 predictions: p-value = 0.7541653131141681

First Derivative: -45.6482848603335*x - 25.8394955091368

Second Derivative: -45.6482848603335

Integral: -7.60804747672224*x**3 - 12.9197477545684*x**2

Conclusions

The article presents an integrated methodology of combining XAI methods with SPC for risk assessment and financial forecasting. The combination of machine learning models with XAI methods such as SHAP and LIME improves the interpretability and transparency of predictive analytics in financial markets. SPC techniques, viz. Shewhart, CUSUM, and EWMA control charts, provide an additional level of monitoring by identifying deviations, anomalies, and systematic shifts in financial indicators. The findings identify that such integration enhances the accuracy of financial forecasting, and also supports active risk management through the identification of early warning indicators of market instability. Explainability capabilities affirm that such stakeholders as policymakers, financial experts, and investors can make knowledge-informed choices from understandable AI-driven insights. Also, the application of differentiation techniques to study the rate of change in financial indices provides important points of instability that supports enhanced decision-making and strategic financial planning.

Future studies can focus on the development of finer integration of deep learning models and state-of-the-art XAI methods to enhance predictive performance without compromising interpretability. The inclusion of real-time adaptive SPC techniques can enhance anomaly detection capacity with dynamic flexibility based on changing market conditions.

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Additionally, using reinforcement learning with SPC may yield more adaptive and self-updating financial prediction systems. Expressing into hybrid approaches that blend the conventional econometric models with insights from AI might also provide a more solid structure for financial analysis. Raising the scope to include multi-factor risk estimation models such as macro-economic factors, geopolitical factors and industry-specific trends could enhance the integrity of risk forecasts. Apart from that, using blockchain-based explainability structures for financial openness and auditability could also help build stronger trust in AI-driven financial systems. The future of financial forecasting is building more interpretable, adaptive and robust AI models that not only forecast market direction but also provide meaningful explanations to assist decision-makers in justifying financial risks effectively.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Parag Puranik, Rahul Pethe, Abhay Kasetwar

Acquisition, analysis, or interpretation of data: Parag Puranik, Abhay Kasetwar

Drafting of the manuscript: Parag Puranik, Rahul Pethe, Abhay Kasetwar

Critical review of the manuscript for important intellectual content: Parag Puranik, Rahul Pethe, Abhay Kasetwar

Supervision: Abhay Kasetwar

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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