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A Survey-Driven Ensemble Approach to Predicting Sovereign Debt Distress in Bangladesh

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Abstract

Operating out of a new, perception-aware machine-learning method of predicting probability of sovereign debt crisis, we integrate survey-based predictors along with existing ensemble classifiers. Out of a purposive sample of 650 Bangladeshi government officials, financial analysts, academics, and students, we extract demographic information, acquaintance with debt concepts, and multi-dimensional risk perceptions in fiscal, political, institutional, and financial dimensions. After categorical conversion via label encoding, treatment of outliers using an interquartile-range filter, Min–Max normalization, and training and testing XGBoost, LightGBM, Random Forest, and weighted soft-voting ensemble via five-fold time-series cross-validation regimen, we demonstrate that the ensemble model has the highest cross-validated training accuracy (0.9528), the same as optimal test accuracy (0.8481), and has weighted F1 score of 0.847, outperforming individual learners and having narrow train–test gap (0.1046). Exploration of the confusion matrix reveals high classification in all five classes for crisis likelihood with specific strengths in classification of “Moderately Likely,” “Likely,” and “Very Likely” outcomes. Adopting the direct incorporation of stakeholder judgments in prediction algorithms, the present study generalizes beyond the usual, data-driven sovereign-risk models and offers an early-warning system via the incorporation of quantitative as well as qualitative characteristics of debt distress. Our research is summed up with the policy implications for proactive risk management as well as sketching the future perspectives, e.g., the leveraging of alternative data streaming in real-time as well as federated learning architecture.

Keywords: *Sovereign Debt Crisis, Machine Learning, Survey-Based Risk Perception, Ensemble Classifiers, Early-Warning System, Bangladesh.*

I. INTRODUCTION

Sovereign defaults continuously demonstrated their capacity of shattering the economy, destabilizing finance markets, as well as dismantling social welfare, particularly in frontier markets as well as emerging markets where fiscal buffers as well as institutional protection can deteriorate. Conventional early-warning indicators, using the econometric methodologies as well as the rating-agency customs, for decades directed policy-makers as well as investors regarding incipient debt-distress phases. Yet the indicators largely rely on historical macro-financial variables or observable aspects in markets, which constrain them in the handling of fast-evolving vulnerabilities as well as in the consideration of the sophisticated analyses of the varied groups of stakeholders (Petropoulos et al., 2022; Alaminos et al., 2021).

Machine learning (ML) has revolutionized financial risk-forecasting in the past few years with the power to utilize high-dimensional data and compute sophisticated, nonlinear relationships. Work by Belly et al. (2023) as well as that of Overes and van der Wel (2023) has demonstrated that tree-based ensemble as well as gradient-boosting machine strategies can notably outperform time-series models in out-of-sample sovereign-risk prediction. Parallel progress in credit-risk prediction as well as in firm-distress prediction has demonstrated the applicability of boosting, bagging, as well as meta-learning approaches to enhance predictive power as well as robustness (Bello, 2023; Jabeur et al., 2020). However, despite these advances, existing ML-based sovereign-risk models remain grounded in quantitative financial as well as macroeconomic information, without regard for subjective opinion that can predict risk sentiment changes or the success of policy.

This study fills that glaring gap by integrating survey-based indicators of fiscal, political, institution, and societal views under a rich ML environment. With the assistance of a purposive sample of 650 Bangladeshi government officials, finance experts, academicians, and students, we borrow a rich feature space including demographic data, experience of the debt concept, and multi-dimensional risk views. After the treatment with labeling encoding, removal of outliers, and min–max scaling of the data, the prediction accuracy of XGBoost, LightGBM, Random Forest, and weighted soft-voting ensemble is estimated under the five-fold time-series cross-validation setting. With the incorporation of the views of the stakeholders in our very model, we put the horizon of the prediction of the risk of the sovereign much further ahead, suggesting an early-warning system, which is quantitatively valid as well as context-aware.

The rest of the paper is laid out as follows. Section 2 reviews the literature on applications of ML in credit risk as well as sovereign risk, citing methodological advances as well as existing lacunae. Section 3 outlines our research design, survey method, as well as the data-processing pipeline. Section 4 includes the model results, comparative analysis, as well as interpretive commentary. Lastly, Section 5 concludes with policy implications, research limitations, as well as prospects for additional research using real-time data streams along with federated learning in further enhancing sovereign-risk monitoring.

II. LITERATURE REVIEW

Machine learning has quickly accelerated the pace of sovereign risk forecasting, extending earlier econometric and rating-based approaches. Belly et al. (2023) first demonstrated the deployment of tree-based learners for the prediction of Euro-area sovereign spreads, citing XGBoost and Random Forest models as superior to more traditional time-series techniques for out-of-sample accuracy. Petropoulos, Siakoulis, and Stavroulakis (2022) furthered these results in constructing a sovereign default early warning system, deploying gradient boosting on macro-financial indicators, and providing timely warnings before the onset of market distress. Alaminos et al. (2021) also deployed support vector machines as well as neural networks for the prediction of currency as well as debt crises, citing nonlinear classifiers as essential for modeling nonlinear sovereign behavior. De Oliveira Campino et al. (2021) as well as Overes and van der Wel (2023) further demonstrated the application of ensemble techniques—the combination of Random Forest, of gradient boosting, as well as penalized logistic regresses—to credit-rating downgrade prediction as well as debt-service stresses with marked increases in predictive capability. Toseafa (2018) first integrated the combination of meta-learning for sub-sovereign credit defaults, before more detailed research by Dong, Liu, and Tham (2024) on the benchmarking accuracy of numerous algorithms in financial-risk applications. Overall, the above studies provide a solid foundation for machine-learning-based sovereign-risk monitoring, but all fundamentally rest upon hard financial information as well as past crises.

Complementary bond-rating and credit-risk studies research has completed the debt-distress-prediction methodological toolkit. Bello (2023) and Kiran et al. (2023) provided in-depth comparations of boosting, bagging, and neural-network credit scorers for retail as well as corporate credit, noting calibrated LightGBM systems generating fair discrimination with moderate overfitting. Umeorah et al. (2024) as well as Suhadolnik, Ueyama, as well as Da Silva (2023) provided real-time credit-risk alert systems, integrating data-stream processing using cost-sensitive decision trees to extract early-warning indications of defaults. Noriega, Rivera, as well as Herrera (2023) as well as Shi et al. (2022) provided systematic reviews of credit-risk ML, noting increased application of explainable models as well as of econometric-and-data-driven learning model hybrids. Munkhdalai et al. (2019) as well as Mhlanga (2021) demonstrated that inclusion as well as socioeconomic indicators—in particular, remittance flows as well as financial-inclusion indicators—that were previously neglected in credit scores, boost the power of credit scores in emerging markets, inviting increased feature sets. Duan et al. (2022) as well as Cui, Zhang, as well as Liu (2024) also noted that combining macroeconomic indicators using firm-level indicators in neural networks as well as ensemble machines improves bond-default forecast accuracy as well as volatility forecast accuracy in financial markets substantially.

Outside sovereign contexts and off-balance-sheet credit, financial-distress and systemic-risk analysis has been revolutionized by machine learning. Samitas, Kampouris, and Kenourgios (2020) challenged widespread financial crises with support-vector machines and neural ensembles and showed early warnings in high-level economic indicators and market sentiment co-predict, each of them independently. Kou et al. (2019) proposed network-based systemic-risk indicators property using graph-neural-networks, considering interbank interconnectivity and contagion channels. Addy et al. (2024), Abdulla and Al-Alawi (2024), and Bazarbash (2019) reviewed fintech and risk-management applications of machine learning and highlighted the potential of real-time sentiment, alternative-data feeds, and federated learning. Abikoye and Agorbia-Atta (2024) and Nwaimo, Adegbola, and Adegbola (2024) showed the possibilities to leverage the population under-banked in credit-access applications and utilized clustering and ensemble classifiers to enhance financial inclusion. Gu, Kelly, and Xiu (2020) elaborated the empirical asset-pricing applications of regularized trees and boosting for extracting factor premia, in order to obtain knowledge of the sovereign-risk premia in global portfolios. Agarwalla (2024) and Malik et al. (2024) also compared the performance of the ML methods with the typical regression methods in stock-returns as well as in the context of detecting financial fraud, as per the trend towards data-driven finance in finance in general.

Cross-field applications have corroborated the risk-prediction potential of ML in industries other than finance. Barboza, Kimura, and Altman (2017) and Huang and Yen (2019) compared machine learners to forecast corporate bankruptcy and demonstrated ensemble learners to outperform logit-based discriminant analyses consistently. Weng et al. (2017), Gusev et al. (2021), Liu et al. (2023), and Benedetto et al. (2022) applied the same methodologies for cardiovascular- and surgical-mortality risk and reported random forests, boosting, and neural nets to dominate established clinical scores. Barker et al. (2022) and Singh et al. (2022) transferred the same to sudden cardiac death and stock-market volatility, respectively, demonstrating feature-selection techniques and cost-sensitive learning to repress false alarms. Mukhanova et al. (2024) and Zhu et al. (2023) applied deep and ensemble learners to financial accounts, while Alonso and Carbo (2020) analyzed the regulatory-cost of predictive performance versus compliance costs. These applications outside the industry hint at the transferability of ML but indicate reliance on numerical and real-time markets data, with less regard for impression or governance-mandated variables.

III. KNOWLEDGE GAP

Despite the opulence of ML deployments to sovereign-risk and credit-risk forecast, existing research extensively uses macroeconomic, market, and firm-level data—perceiving risk as an external, quantifiable phenomenon. Neglected is the development of inputting stakeholder perceptions—collected through survey tools on fiscal, political, institution, and societal aspects—into sovereign-risk models. No such attempt heretofore has combined demographic and behavioral metrics (e.g., public debt awareness, political instability views, confidence in parliamentary oversight) with ensemble-based ML and time-series cross-validation to the forecasting of the risk of sovereign-debt distress for a country. Our research closes this gap uniquely with the use of the full survey-driven feature set for Bangladeshi stakeholders, label-encoding and outlier handling before normalization, and the rigorous benchmarking of XGBoost, LightGBM, Random Forest, and a weighted soft-voting ensemble under a five-fold time-aware configuration. This is a departure from convention in the literature in the use of a strictly numerical data set, canonizing subjective risk views in the form of input directly into predictive models. Through it, we introduce a new, hybridized methodology combining quantitative and qualitative risk markers—enabling richer, context-specific early warnings of sovereign crisis risk that no prior ML-based sovereign-risk study has been able to produce.

IV. RESEARCH METHODOLOGY

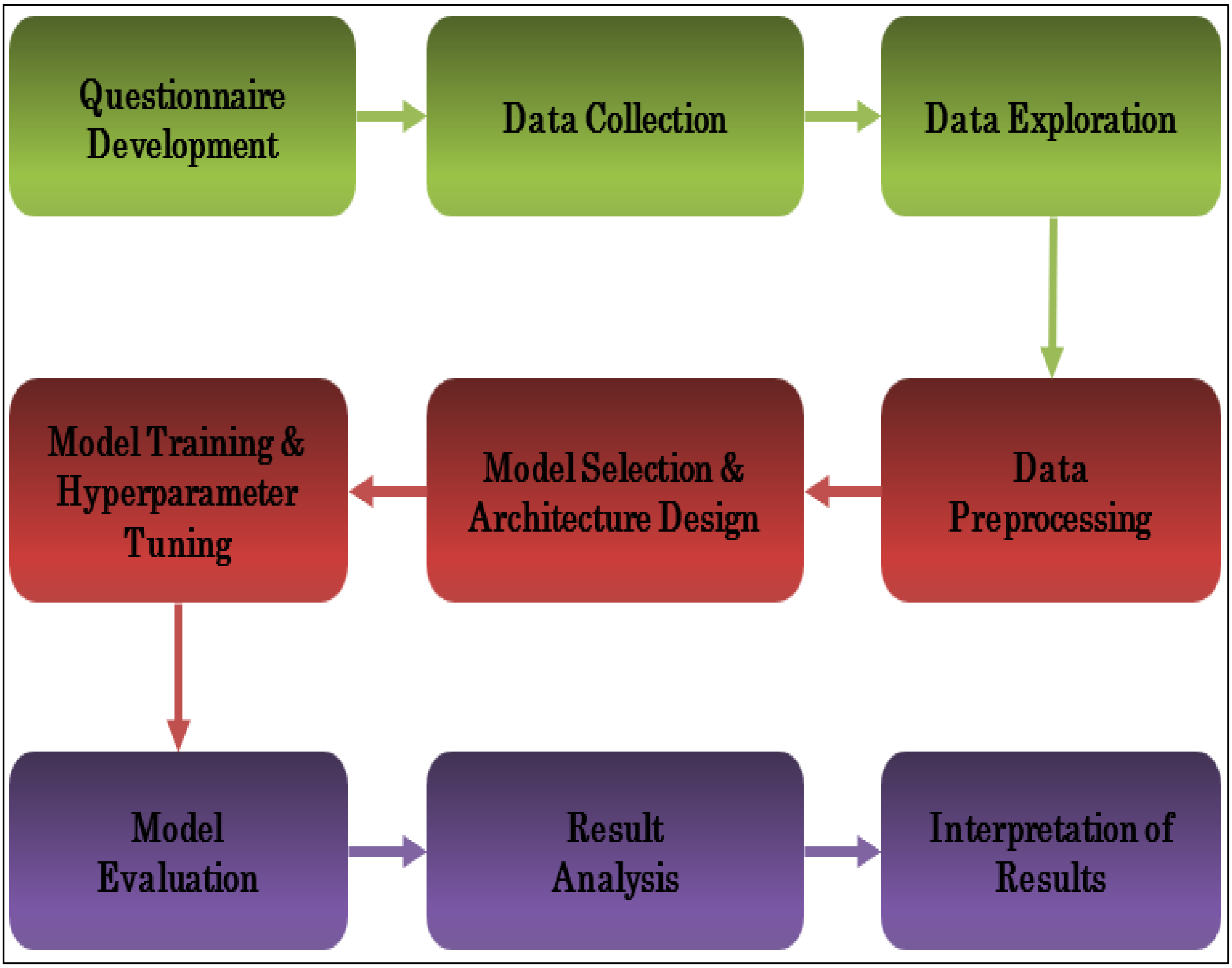

Fig 1 Methodology Flowchart

This research utilizes a descriptive, quantitative method in investigating attitudes of risk of sovereign debt crisis in Bangladesh. The survey aimed at the most important stakeholder groups — government officials, financial experts, university lecturers, as well as students — in order to determine the extent to which demographic, economic, political, as well as institutional attitudes affect expectations of vulnerability of sovereign debt. The research design dwelled on various key dimensions: fiscal as well as economic risk factors, political as well as governance indicators, financial system vulnerability, institutional response capability, as well as public awareness of the issues of debt. The key outcome variable was the respondent's self-rated chances of the occurrence of sovereign debt crisis in the subsequent three years, measured on a five-point Likert scale.

- *Selection of Survey Participants*

Respondents were randomly selected from the cross-section of Bangladesh society, involving government officials, financial experts, academic professionals, as well as university students, in hopes of achieving a broad-based dataset that is representative. Inclusion factors involved the age of above 18 years, enrollment in or ownership of tertiary education, as well as voluntary participation consent. Purposive sampling was applied in the sampling of 650 respondents, in hopes of allowing the samples to remain varied, in terms of age, sex, educational levels, as well as professional experience. This sample size was utilized in hopes of allowing statisticians to perform analysis that is relevant statistically, as well as extract insights that can generalize for relevant populations participating in public financial arguments.

- *Developing and Pre-Testing the Questionnaire*

The survey questionnaire was created to measure perceptions of the risk of sovereign debt in Bangladesh using a multi-dimensional lens. It comprised 25 core items that were intended to capture public views on fiscal, political, institutional, financial, and governance-related factors, as well as familiarity with the risk of crisis, along with risk perception. All items were derived from existing international protocols and expert-based tools, including ones from the IMF, World Bank, Transparency International, as well as various sovereign risk and governance evaluation tools. Six thematic categories were created by grouping the items for the following: Macro-Economic Perceptions, Political and Institutional Factors, External and Financial Risk Factors, Governance and Policy Response Capability, Familiarity with the Risk of Crisis, as well as the perceived risk of crisis occurring in the next three years.

The majority of the items utilized the 5-point Likert scale, whereby the respondent was able to indicate his or her agreement or perceived probability of equal subtlety—from "Strongly Disagree" to "Strongly Agree" or "Very Unlikely" to "Very Likely" as the question context warranted. To check for clarity, appropriateness, as well as congruity with the research objectives, the pilot questionnaire was pre-tested utilizing the varied group of people, which included university students, university employees, government officials, as well as finance experts. Issues of clarity of the terms, generality of particular items, as well as lack of people's acquaintance with response mechanisms of the Likert scale were comments obtained during the pre-test. Thus, the items were reworded in order to fine-tune question wording, incorporate logical flow, as well as simplify the jargon. This pre-testing stage worked towards ensuring the end survey instrument was inclusive, clearly comprehended by the research participant, as well as capable of obtaining the sought information with precision as well as accuracy.

- *The Pilot Study*

Then, pilot survey was administered in April of 2025, in the hopes of piloting the survey instrument in case of the order of the questionnaire, question wording, as well as the design of the survey instrument. 30 university students, 10 lecturers, 5 govt. officials, along with 10 financial professionals, in total, 55 people were engaged and were provided with the questionnaire in English as well as in Bangla. Pilot study helped in the determination of confusion or problem in the question interpretation so as to establish the questionnaire was actually measuring what was intended as well as if relevant variables were included. Pilot study results showed difference in the wordings as being too broad-based as well as unawareness of the Likert-system scale, among the responses.

- *Final Survey Instruments and the Scale of Measurement*

Last survey was administered in the English language accompanied by seven sections, i.e., Demographics, Fiscal as well as Economic Factors, Political as well as Institutional Factors, Financial as well as External Danger Factors, Governance as well as Policy Response Capability, Familiarity as well as Danger Perception, as well as Crisis likelihood in the subsequent 3 years. Demographics section had information pertaining to the age, sex, highest educational achievement, present major function, scholar credentials, as well as awareness of the debt concept. How probable it was going to take place that Bangladesh was going to experience for sovereign debt crisis in the subsequent three years. Responses were scaled throughout the 5-point Likert scale of "Very unlikely" to "Very likely". Most of the questionnaires did employ the 5-point Likert scale with the response of "Strongly Disagree" to "Strongly Agree," while demographic questionnaires were reserved at the end of the survey in order that the respondent maintain the concentration towards the broader research goal in the earlier phases. Last survey instrument was made easy, brief, as well as simple to comprehend, in order to collect correct as well as credible data.

- *The Survey Process*

The entire questionnaire was made online using Google Forms for the comfort of reachability as well as response. The survey link was forwarded via email as well as as social networking, inviting the govt. officials, financial experts, academicians, as well as the students of the university in Bangladesh. Respondents were properly informed of the aim of the research as well as the anonymity of the response. In four months (April–July 2025), 650 valid responses were received. Online administration provided the respondent with the freedom of completing the survey at his or her convenient time, receiving maximum response as well as overcoming the issue of reachability. Facilitations in the form of email or messaging sites were provided for the respondent who faced difficulty in reading the question in order to release the confusion. With the large sample size as well as the administration of the survey using the web, the data collection became rock-solid, research findings becoming statically rigorous as well as representative of the target populace.

V. RESEARCH RESULT AND DISCUSSION

The questionnaire responses were pre-processed using Python through the Google Colab system, with the aid of packages like Pandas, NumPy, as well as SciPy, for pre-processing of the data, calculation of the measures of stats, as well as visualization. Summary of participant response, as well as gaining an insight of the dataset, was achieved using descriptive measures in the form of frequency as well as percentage descriptive measures. Labeling, treatment of the outliers, normalization, as well as supervised machine learning using the XGBoost, the LightGBM, the Random Forest, as well as the vote-based ensemble classifier, were further employed for pre-processing of the data. Performance of the model was further assessed using five-fold Time Series Cross-Validation, using accuracy, precision, the recall, as well as the measure of the F1, as the evaluation measures that were utilized. Analysis revealed the presence of strong prediction linkages between fiscal, political, institutional, as well as financial perception variables, as well as perceived, in the subsequent three years, by the participant, of the occurrence of the sovereign debt crisis.

The survey sample was representative of the wide-based inclusive pool of survey respondents in terms of sex, age, education, occupation, as well as academic achievement. Such inclusiveness was deliberate, aimed at obtaining opinions on the issue of sovereign risk of debt from surveys of different amounts of policy experience as well as industry exposure. Table 1 presents the summary of the salient demographic variables of the 650 surveys involved in the research study.

Table 1 Demographic Data

Demographic Characteristics	Items	Frequency	Percentage
Age Range	18-24	264	40.62
	25-34	189	29.08
	35-44	60	9.23
	45-54	95	14.62
	55+	42	6.46
Gender	Male	342	52.62
	Female	308	47.38
Highest Education Level	Bachelor’s degree	302	46.46
	Master’s degree	221	34.00
	MPhil/PhD	127	19.54
Current Primary Role	University student	416	64.00
	University faculty/researcher	144	22.15
	Government official	9	01.38
	Central bank staff	23	03.54
	Private-sector financial professional	58	08.92
Academic Background	Economics/Finance	286	44.00
	Public Policy/Administration	50	07.69
	Business/Management	314	48.31
Debt Concept Familiarity	Moderately familiar	178	27.38
	Very familiar	206	31.69
	Extremely familiar	266	40.92

The aim of this research was to illustrate the capability of machine learning algorithms in monitoring as well as predicting the threat of debt crises of the sovereign sort according to survey-based indicators. Analysis was carried out in various steps, beginning with the preprocessing of information, treatment of outliers, normalization, and lastly, training as well as testing of four various machine learning algorithms, i.e., XGBoost, LightGBM, Random Forest, as well as an Ensemble Voting Classifier.

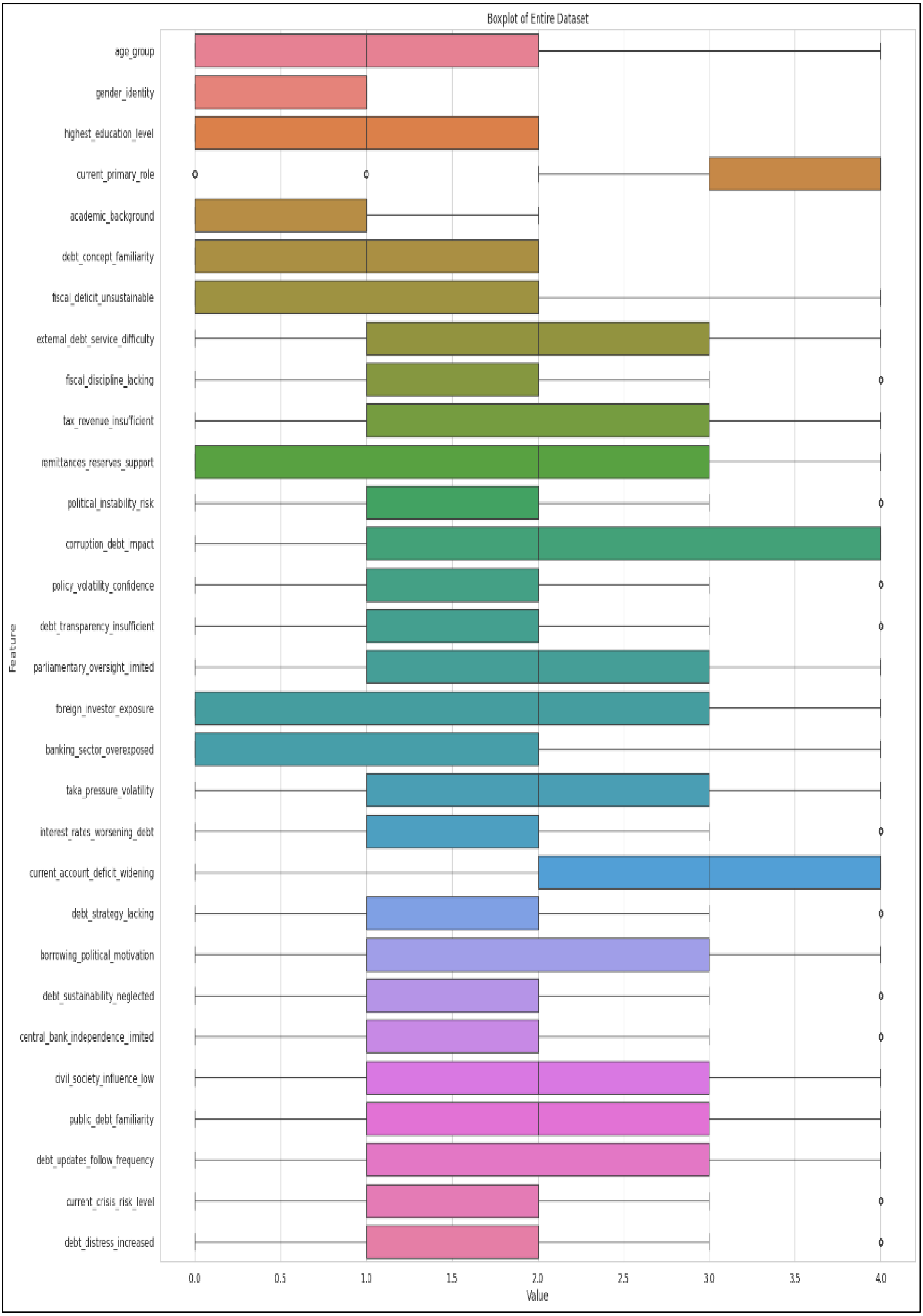

Fig 2 Boxplot Before Removing Outliers

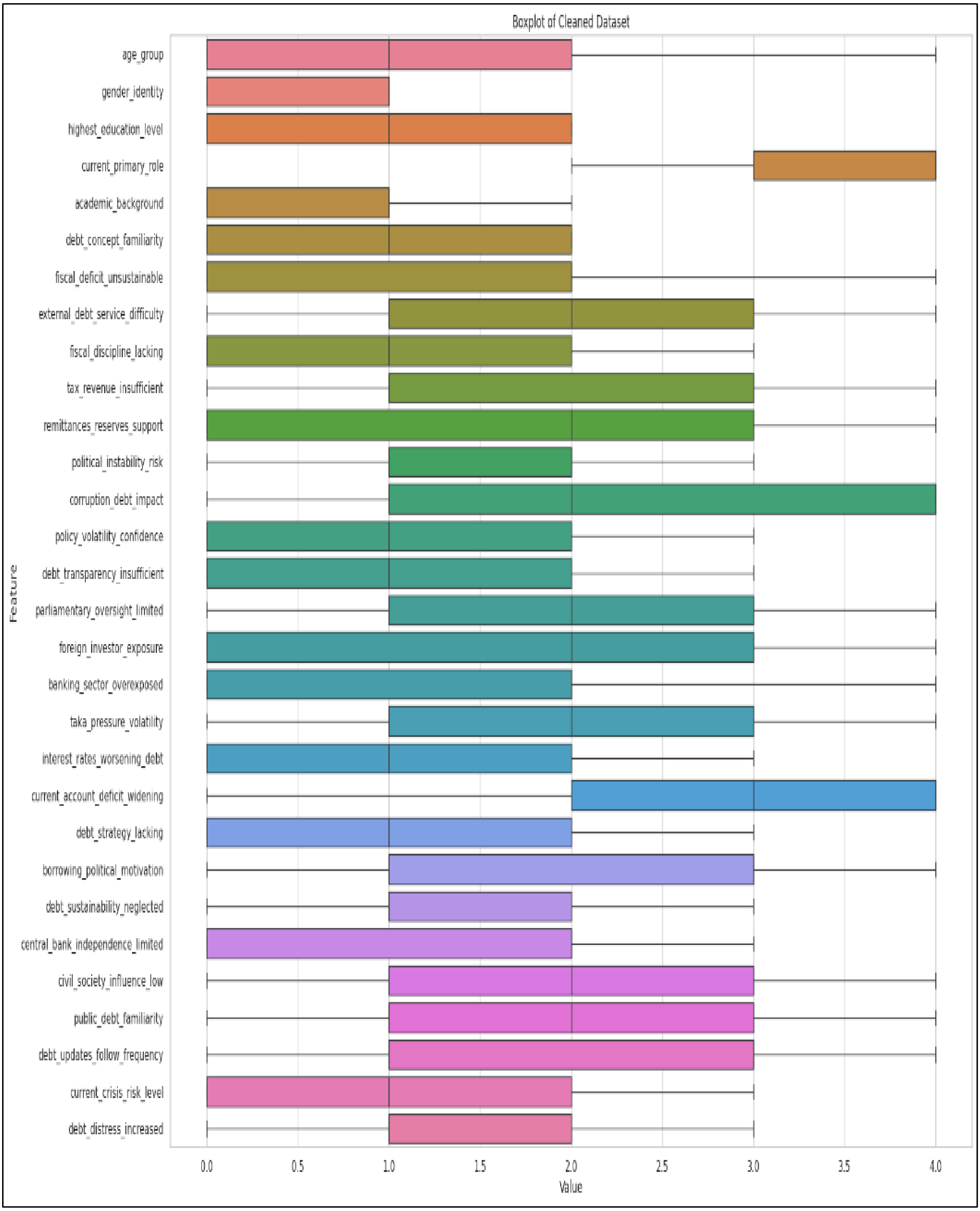

Fig 3 Boxplot After Removing Outliers

First, the dataset was imported and label-encoded in order to transform the categorical features into numerical representations that can be handled by machine learning algorithms. However, the raw dataset's distribution was first observed using the boxplot (shown in Figure 2) to identify the presence of outliers in the features. Outliers were subsequently handled using the interquartile range (IQR) method, in which values outside the specified limits were replaced by `NaN` and hence ignored during training by implication. A second boxplot (shown in Figure 3) was thereafter created to check the better distribution of the dataset after the removal of outliers using the IQR method. This clean dataset was normalized using the Min-Max scaling method to ensure all features were reduced to a similar scale, which is of critical importance for tree-based learners like XGBoost and LightGBM to perform best.

For model performance evaluation, we created a powerful cross-validation setup in the form of five-fold Time Series Split. This was for taking care of potential temporal relationships existing in the data of sovereign risk, given the realization of particular patterns forming along the time passage. Models were calibrated on prior folds for each split, holdout folds for the purposes of evaluation, given the lack of data leakage across the temporal divides. Performance was recorded in terms of exhaustive evaluation measures of training along with test accuracy, precision, recall, F1-score, as well as confusion matrices.

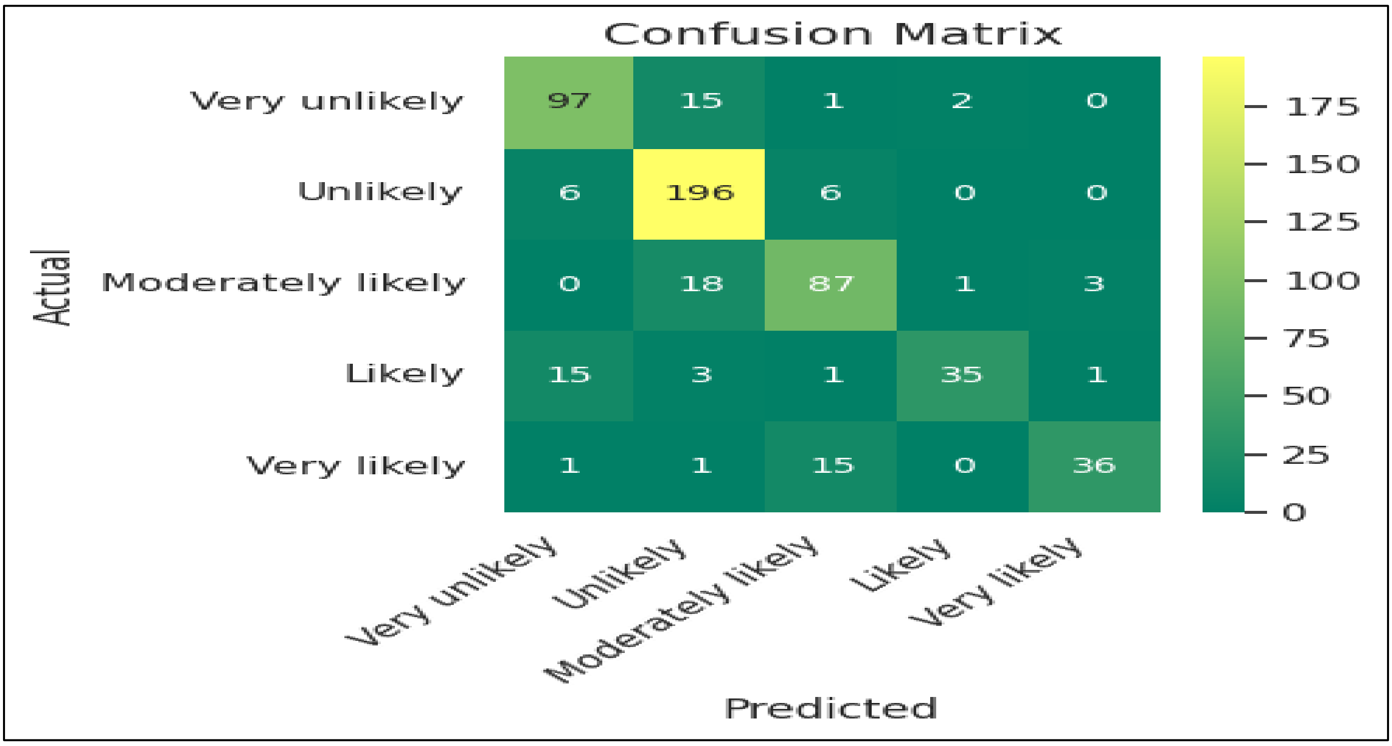

Fig 4 XGBoost Confusion Matrix

XGBoost classifier obtained the average training accuracy of 0.9447, as well as the average test accuracy of 0.8352, in the five-fold case. It obtained the weighted precision of about 0.839, the recall of 0.835, as well as the F1 score of 0.832. Their corresponding confusion matrix (which is given in the form of Figure 4) has relatively equal predictive power for all of the five classes of crisis likelihood, with the highest precision for the “Unlikely,” as well as the “Very Likely,” classes.

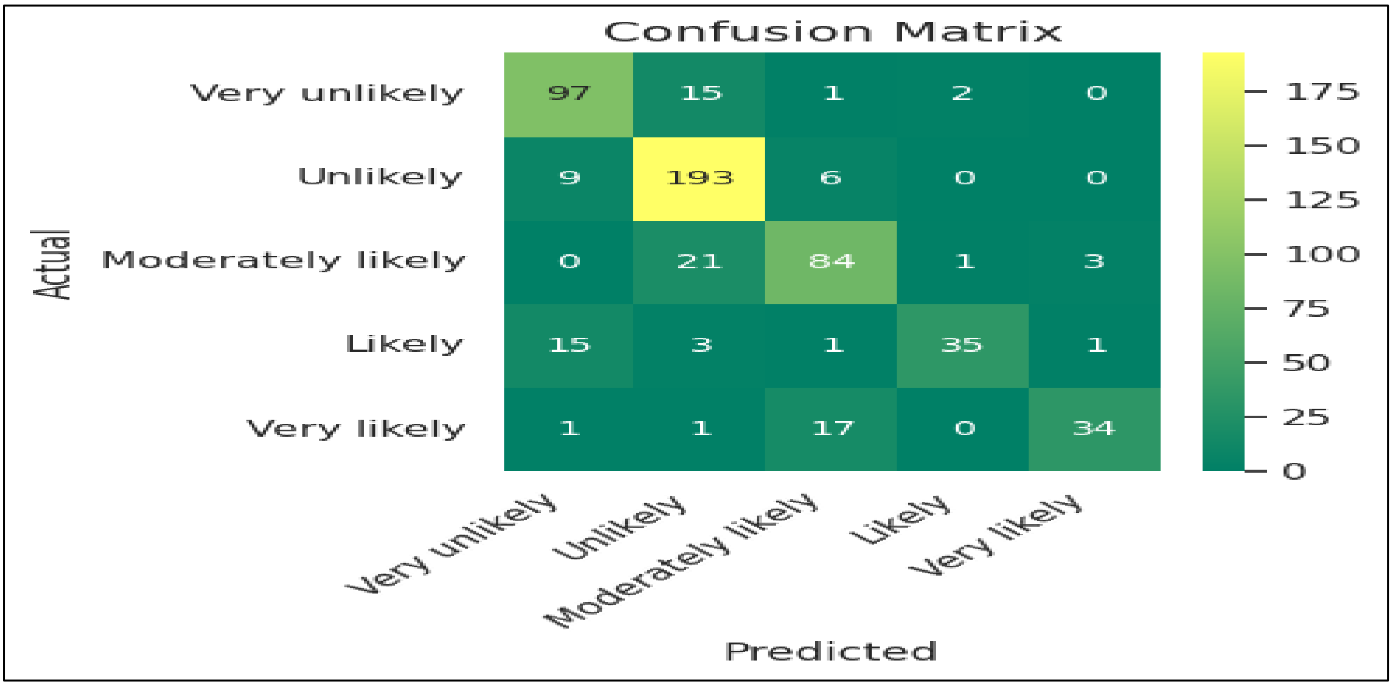

Fig 5 LightGBM Confusion Matrix

Classification accuracy of the LightGBM model was consistent, achieving, on average, training precision of 0.9452 as well as average precision of the test set of 0.8204. Precision, recall, as well as the F1 score, were also estimated at around 0.826, 0.820, as well as 0.817, respectively. Their related confusion matrix (Figure 5) also showed consistent classification performance at the above various chances, with high recall of the "Unlikely" class as well as moderate classification of "Likely" as well as "Very Likely" events.

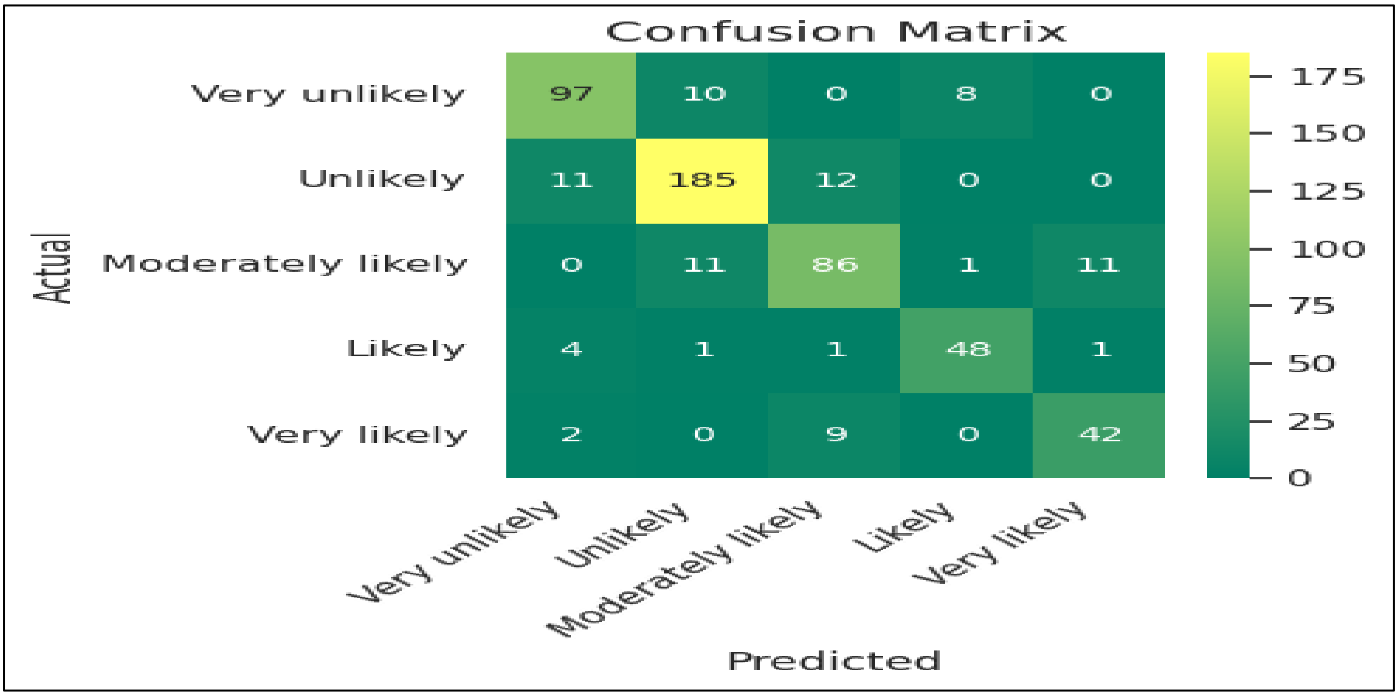

Fig 6 Random Forest Confusion Matrix

Random Forest revealed modestly better generalizability, resulting in an average accuracy of 0.9134 on training data and the highest average accuracy of 0.8481 when tested. Though it had lower training score in relation to the boosting ensembles, it was the most stable in the test set. The model obtained the weighted precision of 0.848, the recall of 0.848, as well as the F1 score of 0.848 as well. Confusion matrix for this model (Figure 6) revealed the consistent performance of the model for all the classes, with the exceptionally high performance in the "Unlikely" as well as the "Likely" class, showing superior capability of retrieving the low as well as the high-risk cases.

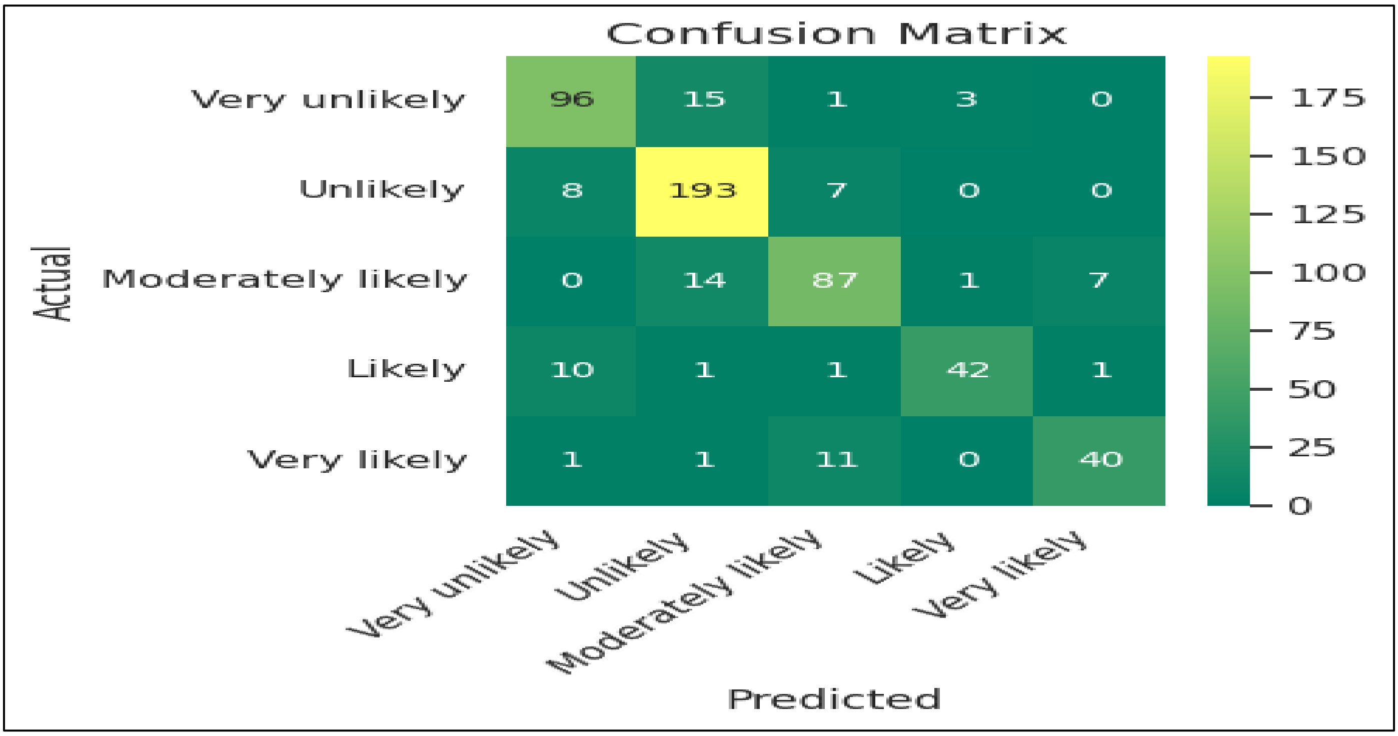

Fig 7 Ensemble Model Confusion Matrix

Lastly, the ensemble vote classifier was defined as the combination of the XGBoost, the LightGBM, as well as the Random Forest classifier using the soft vote, with the weights assigning the highest priority to the Random Forest classifier (0.6) in comparison to the remaining two of 0.2 each. It had the best mean training accuracy of 0.9528 as well as tied the random forest accuracy of 0.8481 in the tests. It had the weighted precision of 0.849, the weighted recall of 0.848, as well as the weighted score of the F1 of 0.847. The related confusion matrix (Figure 7) demonstrated superior detection of the "Moderately Likely," "Likely," as well as the "Very Likely" classes, which shows the ensemble method functioned to neutralize the strengths of the model's base classifiers.

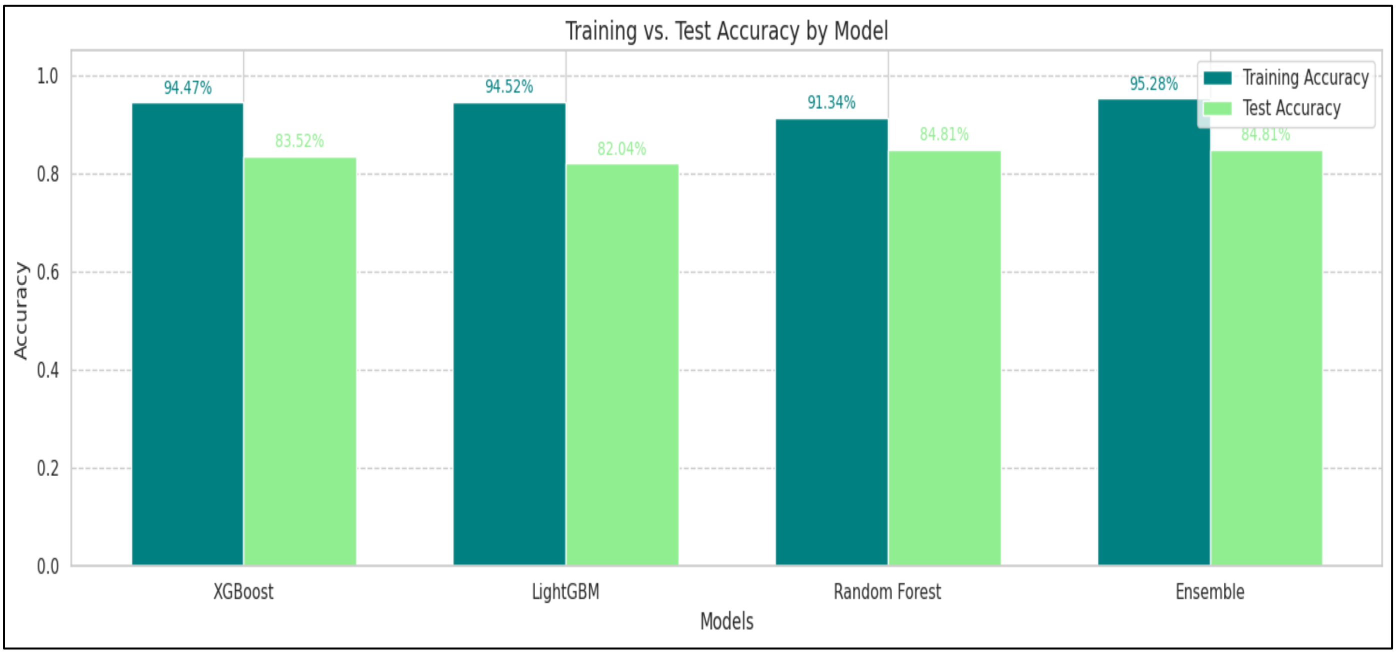

Fig 8 Train and Test Accuracy Comparison

For visualization and comparison of the model's performance, the bar graph showing training as well as test accuracy of all four models is given in Figure 8. Bar graph stresses the consistency of the Random Forest as well as the Ensemble classifier that had kept the difference between training as well as testing performance relatively low throughout the classification task. However, the boosting models, although achieving the higher training accuracy, had kept the generalization gaps slightly larger, demonstrating the overfitting tendency of the configurations in these particular models.

Overall, all the models revealed adequate prediction capability in the given sovereign risk categories, thus the survey-based indicators, when duly processed as well as modeled, can present informative information on the risk of sovereign debt distress. Cross-validated assessment procedure, furthermore supplemented by the same findings of the various applied models, as well as the several measurement-based measures, attest towards the validity of the results applied in the time-aware prediction of sovereign risk.

VI. CONCLUSION

Among the learners, the best risk of the prediction model of the sovereign debt crisis was the ensemble of the XGBoost, the LightGBM, as well as the Random Forest learners. With the aid of soft-voting method in favor of the trustworthy generalizability of the Random Forest, the ensemble had the best cross-validated training accuracy (0.9528) as well as tied the all-learners optimal all-learners optimal test accuracy (0.8481). Its weighted precision (0.849), as well as recall (0.848) as well as F1 score (0.847) also suggest the well-balance performance of all of the five crisis-likelihood categories. Its combining capability of various decision thresholds as well as regularization abilities of the base learners helped it in suppressing the overfitting—isomorphic in the relatively smaller train–test accuracy difference—yet obtaining strong classification for the low-risk as well as high-risk categories.

VII. FUTURE WORK

With much higher accuracy and stability of our ensemble model, the venerable room for incrementally refining it is of little hope. Instead, the next horizon of potential is one of fusing in-real-time disparate streams of the like of high-frequency satellite imagery, global trade flows, and social-media sentiment analysis, into the always-learning sovereign-risk AI agent. All of the above, in turn, opens the possibility of combining quantum-optimized designs of neurons with global financial-institutions-based federated learning in order to power truly autonomous, adapting risk monitoring at global scales heretofore unprecedented in size. Such far-horizon potential would see our model take the powerful fore-casting tool it is today, turning it into the self-adaptive sentinel of global financial stability.

➢ *Declaration of Interest Statement*

The authors declare that there is no known financial interest or personal relationships that could have influenced work presented in this paper.

➢ *Data Availability*

Survey Based Data on Sovereign Debt Risk Likelihood in Bangladesh.

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