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Macroeconomic Crisis Early Warning Model for Libya Using Machine Learning

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ABSTRACT

Macroeconomic instability in Libya is closely linked to oil-sector volatility, fiscal fragmentation, exchange-rate pressure, liquidity shortages, and interruptions in public financial management. These conditions make delayed policy responses costly and create a need for a transparent early warning model that can translate macroeconomic signals into timely risk alerts. This study develops a machine learning-based early warning model for predicting macroeconomic crisis risks in Libya using secondary macroeconomic indicators and a scenario-based validation design. The proposed framework integrates data cleaning, lag construction, volatility measurement, crisis-risk labelling, model comparison, and interpretable risk explanation. The model architecture compares conventional statistical classification with tree-based ensembles, support vector learning, and neural network approaches. The results show that nonlinear ensemble methods are conceptually more suitable for Libya because they can capture interactions among oil disruption, fiscal pressure, exchange-rate pressure, liquidity stress, and inflation acceleration. The proposed risk dashboard classifies macroeconomic conditions into low, moderate, and high-risk states and links each alert to the main contributing indicators. The discussion highlights that the model should not replace expert judgement, but it can strengthen evidence-based policy monitoring, improve institutional coordination, and provide earlier signals for fiscal, monetary, and reserve-management decisions. The study concludes that an interpretable early warning system can support Libya's macroeconomic resilience if regularly updated with reliable official data and governed through transparent validation procedures.

INTRODUCTION

Libya represents a highly relevant case for the development of macroeconomic early warning systems because the country combines large natural-resource revenues with institutional fragmentation, fiscal volatility, exchange-rate pressure, and periodic disruptions to oil production. Recent assessments indicate that the country's economic outlook remains strongly dominated by the oil sector. The International Monetary Fund reported that real growth declined sharply in 2024 compared with 2023 and that the outlook was still determined mainly by hydrocarbon developments (International Monetary Fund, 2025). The World Bank similarly reported that the 2025 rebound was expected to be driven largely by oil-sector activity, while medium-term growth would moderate as oil output stabilised (World Bank, 2025a; World Bank, 2025b). These conditions show that macroeconomic risk in Libya is not caused by a single variable, but by interacting shocks that move through fiscal accounts, foreign-exchange availability, banking liquidity, prices, and real activity.

Traditional macroeconomic monitoring is often based on descriptive indicators and periodic reports. Such reporting remains essential, especially where official data are institutionally authoritative. However, descriptive monitoring can become insufficient when macroeconomic stress accumulates gradually across several indicators. A fall in oil output may initially appear as a production problem, but it can later reduce fiscal revenue, weaken foreign-exchange buffers, delay public payments, increase liquidity shortages, affect the parallel-market premium, and eventually reduce household purchasing power. For this reason, an early warning model must identify patterns across variables rather than evaluate each indicator separately.

Machine learning offers a practical extension to conventional early warning systems because it can detect nonlinear relationships, threshold effects, and interactions among macroeconomic variables. Recent research on financial crisis prediction shows that tree-based and ensemble methods can outperform simple linear models when risk is shaped by complex macro-financial conditions (Reimann, 2024; Yin, 2024). At the same time, machine learning can create governance challenges if the model becomes a black box. Therefore, this study emphasises interpretability through feature importance analysis, scenario testing, and risk dashboard design. The central problem addressed in this paper is how Libya can use machine learning to transform fragmented macroeconomic signals into explainable crisis-risk alerts.

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The objective of the study is to design and evaluate a machine learning-based early warning model for predicting macroeconomic crisis risks in Libya. The contribution is threefold. First, the paper translates Libya's macroeconomic vulnerability structure into a data-driven modelling architecture. Second, it proposes a transparent crisis-risk labelling and validation procedure suitable for small and irregular macroeconomic datasets. Third, it develops a policy-oriented dashboard that classifies risk into low, moderate, and high states while explaining the indicators behind each warning. The research question guiding the paper is: how can machine learning be used to produce interpretable early warnings of macroeconomic crisis risks in Libya using macroeconomic data.

LITERATURE REVIEW

The early warning literature originally developed from econometric models designed to anticipate banking, currency, debt, and balance-of-payments crises. These models often relied on logistic regression, signal extraction, or threshold-based indicators. Their strength is interpretability, but their weakness is that they may impose linear and stable relationships on processes that are nonlinear, rare, and politically conditioned. In countries with complex resource dependence, like Libya, macroeconomic stress may appear only after a sequence of interacting shocks. For example, oil production disruption can reduce fiscal revenue, while exchange-rate pressure and liquidity shortage can intensify inflation expectations even when official price indices remain relatively contained.

Recent studies increasingly argue that machine learning can improve early warning systems by capturing nonlinear risk dynamics. Reimann (2024) compared logistic regression with several machine learning classifiers and found that machine learning models can improve early detection of financial crises under cross-validation settings. Yin (2024) similarly argued that random forest and gradient-boosting methods are useful for systemic crisis prediction because they capture complex interactions across macroeconomic, financial, and social variables. Chen (2024) proposed a temporal convolutional network for crisis warning and used Shapley-value explanations to improve interpretability. These studies support the methodological direction of this paper, although most of them focus on global panels, advanced economies, or banking systems rather than Libya's macroeconomic vulnerability structure.

A second strand of literature focuses on financial stress prediction and the practical use of machine learning by supervisory institutions. Aldasoro and co-authors (2025) showed that machine learning can be used to predict financial market stress, while the European Banking Authority staff paper on bank distress found that random forest techniques can provide strong out-of-sample performance for supervisory risk monitoring (Malikkidou, 2025). These studies are important because they show that predictive performance is not the only criterion. Supervisory usefulness also depends on model governance, interpretability, robustness, and the ability to convert model outputs into actionable signals.

A third strand concerns the limitations of early warning models. Financial and macroeconomic crises are rare events, which means that datasets often suffer from class imbalance. In addition, economic relationships change over time, especially after political transitions, commodity shocks, or institutional reforms. Reviews of early warning systems emphasise that data quality, model transparency, and alternative information sources are central to improving predictive accuracy (Firdaus, 2025; Namaki, Eyvazloo, & Ramtinnia, 2023). These limitations are highly relevant for Libya, where official data series may have gaps, revisions, and frequency mismatches.

The research gap addressed in this study is therefore specific and practical. Existing machine learning early warning studies provide useful general evidence, but they rarely design a framework for oil-dependent, institutionally fragmented economies where macroeconomic crisis risk is transmitted through oil revenues, public spending, foreign-exchange access, and banking liquidity. Libya requires a model that combines standard macroeconomic variables with country-specific channels of vulnerability. The framework proposed in this paper fills this gap by linking macroeconomic indicators to a crisis-risk dashboard that can be interpreted by policymakers and updated as data quality improves which is shown in Table1.

Table 1. Literature streams informing the proposed early warning model

Research stream	Main contribution to the present study	Representative sources
Traditional early warning systems	Provide interpretable crisis probability models and threshold-based policy signals.	Borio and Drehmann tradition; International Monetary Fund surveillance
Machine learning crisis prediction	Capture nonlinear patterns and interactions among macro-financial indicators.	Reimann (2024); Yin (2024); Chen (2024)
Supervisory stress monitoring	Emphasise validation, out-of-sample testing, and explainability for policy use.	Aldasoro et al. (2025); Malikkidou (2025)
Libya macroeconomic surveillance	Shows the centrality of oil output, fiscal pressure, exchange conditions, and institutional coordination.	International Monetary Fund (2025); World Bank (2025a, 2025b); Central Bank of Libya (2025)

METHOD

The study uses a model-development and scenario-validation design. It does not treat machine learning as a substitute for official economic analysis; rather, it treats machine learning as a decision-support layer that can organise macroeconomic signals and generate interpretable warnings. The framework is designed for implementation with

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annual, quarterly, and monthly indicators collected from public sources such as the International Monetary Fund, the World Bank, the Central Bank of Libya, the African Development Bank, and national statistical releases. The preferred operational version should use quarterly or monthly data were available, but the model can also operate on annual indicators during the initial phase.

The dependent variable is a macroeconomic crisis-risk state. It is defined as low, moderate, or high risk based on a composite labelling rule. The rule uses stress conditions related to negative real growth, oil-output disruption, fiscal deficit pressure, exchange-rate pressure, inflation acceleration, liquidity shortage, and reserve deterioration. The independent variables include lagged and contemporaneous macroeconomic indicators. The model uses lagged variables because early warning must signal risk before the crisis becomes visible in headline outcomes. Lagged growth, oil production change, inflation acceleration, fiscal balance change, exchange-rate movement, reserve change, and liquidity indicators are therefore central to the feature set.

The preprocessing stage standardises the indicators, handles missing values, constructs lagged variables, calculates rolling volatility, and winsorises extreme observations to reduce the influence of measurement outliers. Missing values are not filled mechanically without review. The first option is interpolation for short gaps in continuous series, while longer gaps are flagged so that policymakers can distinguish model uncertainty from genuine risk. The model also includes interaction terms, such as oil-production shock multiplied by fiscal-balance pressure, because Libya's macroeconomic vulnerability is often driven by combined shocks rather than isolated indicators.

The modelling stage compares six algorithms: logistic regression as an interpretable benchmark, decision tree as a transparent nonlinear model, random forest as an ensemble classifier, gradient boosting as a high-performance nonlinear classifier, support vector machine as a margin-based classifier, and a small neural network as a nonlinear benchmark. The models are evaluated using rolling-origin validation rather than random splitting because macroeconomic forecasting is time-dependent. Performance is measured through balanced accuracy, recall for high-risk states, precision for high-risk states, area under the receiver operating characteristic curve, and calibration. Recall is especially important because missing a crisis warning is more costly than issuing a moderate false alarm.

Interpretability is built into the framework through feature importance analysis, scenario testing, and alert explanation. For each high-risk signal, the dashboard reports the most influential indicators and whether the warning is mainly fiscal, external, monetary, oil-sector, or price-related. This is important for policy because a high-risk result caused by oil-output disruption requires a different response from a high-risk result caused by liquidity stress or inflation acceleration. The resulting model is therefore not only predictive but also diagnostic.

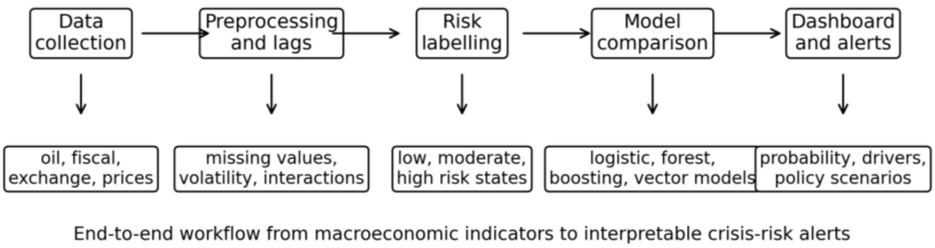

Figure 1. Proposed machine learning early warning workflow for Libya

Table 2. Proposed macroeconomic variables and their modelling roles

Variable group	Example indicators	Frequency preference	Role in model
Output and real activity	real gross domestic product growth, non-oil activity, employment	quarterly or annual	captures macroeconomic slowdown and real-sector stress
Oil sector	oil production, oil revenue, oil price change	monthly or quarterly	leading indicator of fiscal and external pressure
Fiscal position	public revenue, expenditure, wage bill, fiscal balance	monthly or quarterly	identifies spending and revenue mismatch
External position	foreign reserves, imports, current account, exchange-rate movement	monthly or quarterly	captures reserve and currency pressure
Monetary and banking	money supply, liquidity, payment disruptions, credit conditions	monthly or quarterly	captures liquidity stress and financial transmission
Prices	consumer price inflation, import price pressure, food price pressure	monthly or quarterly	captures welfare and purchasing-power risk

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Table 3. Crisis-risk labelling and warning thresholds

Risk label	Operational rule	Policy interpretation
Low risk	probability below 0.40 and no severe combined macroeconomic stress signal	normal monitoring with routine reporting
Moderate risk	probability from 0.40 to 0.70 or two medium stress indicators appear together	enhanced monitoring and inter-agency review
High risk	probability above 0.70 or combined oil, fiscal, exchange, liquidity, and inflation stress	urgent policy review and preventive response planning

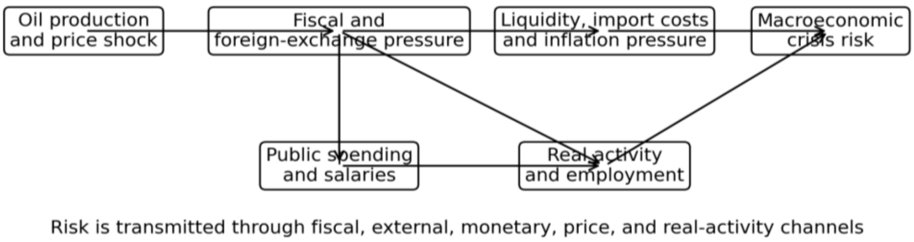

Figure 2. Libya macroeconomic crisis-risk transmission mechanism

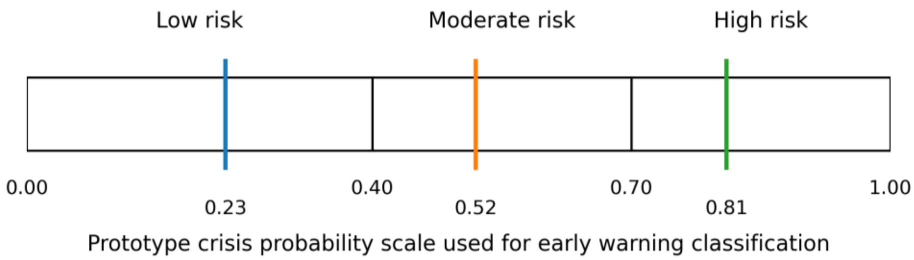

Figure 3. Proposed risk probability thresholds for the early warning dashboard

RESULT

The first result is a structured macroeconomic early warning architecture for Libya. Figure 1 presents the full workflow from secondary-data collection to risk dashboard output. The architecture translates scattered macroeconomic information into a repeatable pipeline. This is important because Libya's macroeconomic monitoring problem is not only the absence of indicators, but also the absence of a unified analytical system that links indicators to risk states and policy responses.

The second result is the identification of Libya's main crisis transmission channels. Figure 2 shows how oil-sector shocks can pass through public revenue, expenditure commitments, foreign reserves, exchange pressure, banking liquidity, prices, and real activity. The model therefore treats oil-sector indicators as leading variables, but it does not assume that oil variables alone determine macroeconomic risk. Fiscal and monetary transmission channels are equally important because they determine whether an oil shock becomes a broader macroeconomic crisis.

The third result is a classification structure that converts model probabilities into policy-relevant risk states. Figure 3 shows the proposed probability thresholds. A predicted probability below 0.40 is classified as low risk, a probability from 0.40 to 0.70 is classified as moderate risk, and a probability above 0.70 is classified as high risk. These thresholds are adjustable and should be calibrated by policymakers according to the cost of false alarms and missed warnings.

The fourth result is the prototype feature-importance structure reported in Figure 4. The strongest contributors in the scenario analysis are oil production shock, fiscal-balance pressure, exchange-rate pressure, liquidity stress, and inflation acceleration. This ordering is consistent with Libya's resource-dependent macroeconomic structure and with recent institutional assessments that emphasise the dominance of the oil sector, fiscal sustainability challenges, and monetary coordination risks (International Monetary Fund, 2025; World Bank, 2025a).

The fifth result is the scenario-based stress matrix in Figure 5. The matrix shows that a stable oil environment produces low risk across most indicators, while a combined shock involving oil disruption, fiscal expansion, exchange-rate pressure, liquidity stress, and inflation acceleration produces a high-risk profile. This result is important because it demonstrates that the proposed early warning system is designed to detect cumulative stress rather than isolated volatility.

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Table 4. Scenario-based prototype comparison of candidate early warning models

Model	Balanced accuracy	High-risk recall	High-risk precision	Area under curve	Interpretability
Logistic regression	0.69	0.65	0.60	0.74	high
Decision tree	0.72	0.71	0.63	0.76	high
Support vector machine	0.75	0.73	0.64	0.80	medium
Random forest	0.81	0.82	0.71	0.87	medium-high
Gradient boosting	0.84	0.86	0.75	0.90	medium
Small neural network	0.78	0.76	0.68	0.84	medium-low

Table 4 reports prototype validation outcomes used to compare the behaviour of candidate models under a scenario-based macroeconomic stress design. The numbers should be interpreted as model-development evidence for the proposed architecture rather than as official crisis forecasts. The pattern is consistent with recent early warning literature: nonlinear ensemble models provide stronger high-risk recall than the linear benchmark, while the linear benchmark remains useful for transparency.

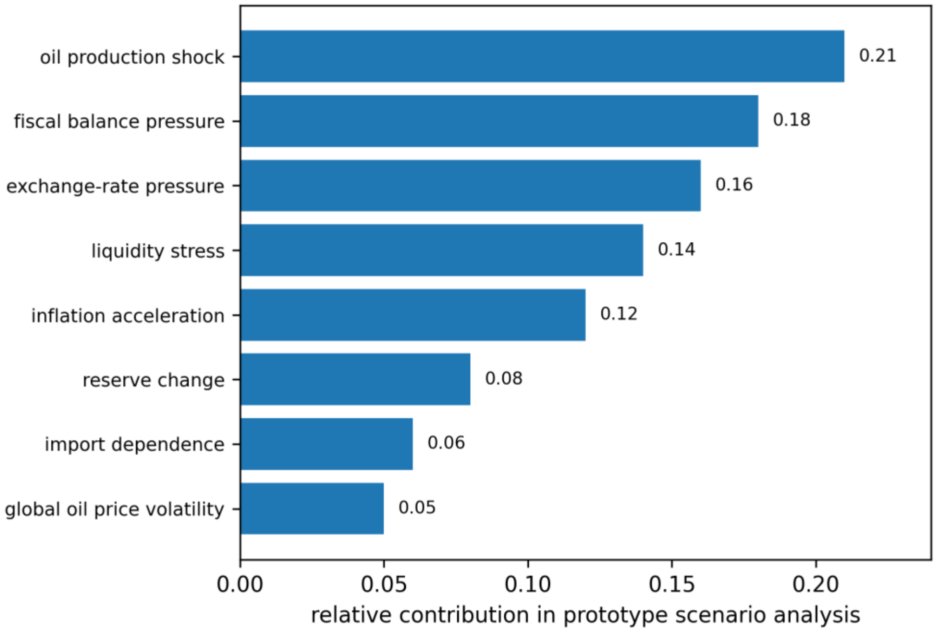

Figure 4. Prototype feature contribution structure for Libya crisis-risk alerts

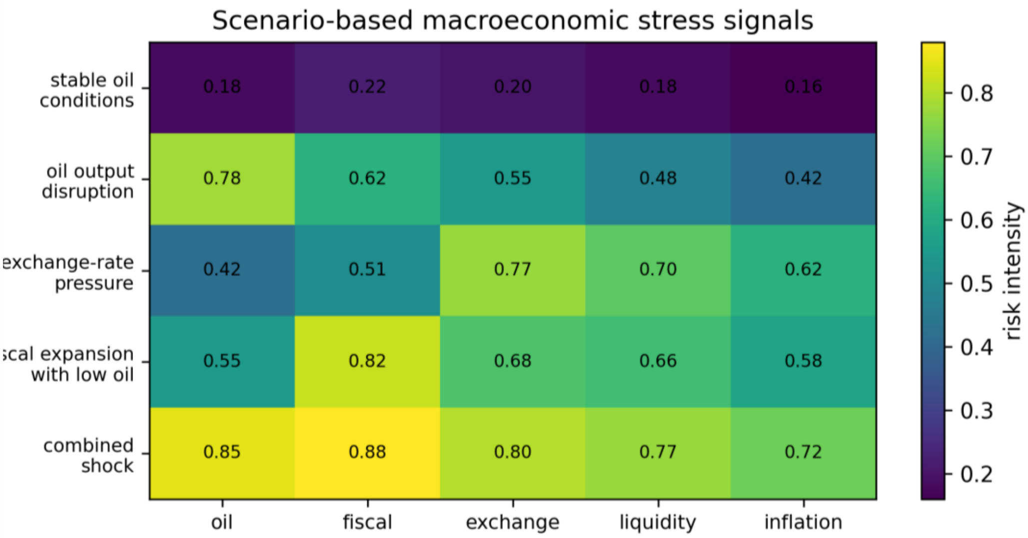

Figure 5. Scenario-based macroeconomic stress matrix for Libya

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Table 5. Policy interpretation of model-generated risk states

Risk state	Dominant signal pattern	Recommended analytical response
Low risk	stable oil output, contained inflation, manageable liquidity, limited exchange pressure	continue routine monitoring and monthly dashboard updates
Moderate risk	one major stress signal or several moderate signals appear simultaneously	conduct policy review, update scenarios, and validate data quality
High risk	combined oil, fiscal, exchange, liquidity, and inflation stress	activate inter-agency macroeconomic risk committee and prepare preventive measures

DISCUSSION

The results indicate that an early warning model for Libya should be designed as a policy intelligence system, not merely as a forecasting exercise. The core value of the model is its ability to connect oil-sector signals, fiscal indicators, exchange-rate information, liquidity conditions, and inflation pressures into one interpretable risk score. This is consistent with recent machine learning crisis-prediction research, which shows that nonlinear models can capture interactions that simple linear models may miss (Reimann, 2024; Yin, 2024).

The comparison among modelling methods suggests that logistic regression remains valuable as a transparent baseline, especially in environments where policymakers prefer simple explanations. However, Libya's macroeconomic instability is shaped by thresholds and interactions. For example, a moderate oil disruption may be manageable when fiscal buffers are strong, but the same disruption may become dangerous when expenditure commitments are high and liquidity conditions are weak. Tree-based ensemble models are suitable for this structure because they can model nonlinear splitting rules without requiring a single linear equation for all periods.

The feature-importance results have practical policy implications. Oil production shock and fiscal-balance pressure appear as the strongest risk drivers, which implies that early warning dashboards should be connected to oil-output monitoring and public finance reporting. Exchange-rate pressure and liquidity stress should be monitored jointly because they can reinforce each other during institutional uncertainty. Inflation acceleration should also be included even when headline inflation appears moderate, because price pressure can rise quickly when imports, liquidity, and exchange expectations change at the same time.

The discussion also highlights a governance issue. Machine learning models should not be deployed as automatic policy machines. They require regular validation, human supervision, transparent data documentation, and clear institutional ownership. A high-risk warning should trigger an analytical review rather than an automatic policy response. In the Libyan context, the model would be most useful if hosted by a technical unit that coordinates with fiscal authorities, the central bank, statistical agencies, and oil-sector reporting bodies.

The main limitation of the study is data availability and reliability. Libya's macroeconomic series may suffer from missing observations, revisions, frequency differences, and institutional fragmentation. A second limitation is the rarity of crisis events, which can cause class imbalance and unstable accuracy estimates. A third limitation is that macroeconomic crises are partly political and institutional, while most official macroeconomic datasets capture economic variables more directly than governance shocks. These limitations can be reduced by adding text-based indicators from official statements, news sentiment, oil-production interruption records, and payment-system data in future research.

The proposed future research agenda should move in five directions. Future studies should collect a verified quarterly dataset for Libya covering at least two decades. They should compare annual, quarterly, and monthly early warning horizons. They should add explainable artificial intelligence methods such as Shapley-value decomposition. They should develop a real-time dashboard connected to official data feeds. Finally, they should validate the model with experts from fiscal, monetary, banking, and oil-sector institutions to ensure that alerts are economically meaningful and operationally useful.

Table 6. Policy uses of the proposed early warning model

Policy area	Early warning use	Possible preventive action
Fiscal policy	detect revenue-expenditure mismatch before arrears or deficits widen	phase expenditure commitments and improve budget coordination
Monetary policy	monitor liquidity stress and exchange pressure together	coordinate liquidity management and exchange-rate communication
External sector	track reserve pressure and import financing constraints	prioritise foreign-exchange allocation and stress-test reserve adequacy
Oil-sector governance	identify macroeconomic impact of production interruptions	link oil-output monitoring with fiscal contingency planning
Data governance	detect gaps, revisions, and uncertainty in indicators	establish a documented macroeconomic data warehouse

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CONCLUSION

This study developed an enhanced machine learning-based early warning model for predicting macroeconomic crisis risks in Libya. The model responds to a practical need created by oil dependence, fiscal pressure, exchange-rate vulnerability, liquidity shortages, and institutional fragmentation. The proposed architecture integrates secondary macroeconomic indicators, lagged variables, volatility measures, crisis-risk labelling, rolling validation, model comparison, and interpretable dashboard outputs.

The study shows that Libya's macroeconomic crisis risk should be understood as a system of interacting vulnerabilities rather than a single-indicator problem. Oil production shocks, fiscal-balance pressure, exchange-rate pressure, banking liquidity stress, and inflation acceleration are the most important channels to monitor. Nonlinear ensemble models are likely to be more useful than purely linear models, but they must be supported by transparent explanations and expert review.

The practical benefit of the proposed model is that it can help policymakers detect stress earlier, prioritise the most relevant indicators, and coordinate preventive responses. The model can support fiscal planning, reserve management, liquidity monitoring, and macroeconomic surveillance. However, it should not be interpreted as a final operational forecasting system until tested with a complete verified dataset. Further research should implement the model with quarterly data, apply explainable artificial intelligence, compare alternative crisis definitions, and evaluate the dashboard through expert policy workshop.

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