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Predicting coups in real time: A 4IR-based Early Warning Framework for the African Union

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Abstract

TThis paper presents an early warning framework that exploits Fourth Industrial Revolution (4IR) technologies that can predict coups in real-time. Coups remain a persistent threat to democratic governance and socio-economic development across African states, exacerbated by civil unrest, political exclusion, and economic instability. Traditional early warning systems often rely on lagging indicators and subjective assessments, limiting their effectiveness in timely prediction and response. This paper proposes a Random Forest machine learning classifier integrated with multi-dimensional data streams, including political, economic, social, security, and regional factors, to deliver dynamic, real-time risk assessments. The framework uses datasets such as governance indicators, economic metrics, ethnic fractionalisation, political inclusion, and military conditions from sources such as the World Bank and regional intelligence reports. Empirical findings highlight that governance quality, political exclusion, economic grievances, and military dissatisfaction are among the most predictive features of coup risk in Africa. The case study of Guinea's September 2021 coup demonstrates how the Random Forest model could have offered early warnings months in advance by analysing converging risk indicators. Despite challenges related to data quality, coverage, and the inherently unpredictable nature of coups, this framework can enhance the AU's

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capacity for proactive intervention and conflict prevention. Human oversight remains essential for mitigating ethical concerns and ensuring contextualised interpretation. This work contributes to peace-building by providing a scalable, data-driven tool aligned with the AU's Agenda 2063 and offers a path toward more effective, technology-enabled political stability monitoring.

***Keywords*:** *Coups; Conflict; Fourth Industrial Revolution; Early warning; Africa; Random Forester*

Introduction

The African Union (AU) has continually faced significant challenges in maintaining political stability among its member states, with coups d'état representing a persistent threat to democratic governance and socio-economic development (Birhan, 2024; Eizenga, 2022). The prevalence of civil unrest, with some countries like the Sudan and the Democratic Republic of the Congo having not known any peace dividend since attaining independence, partisan rejection of constitutional norms, and instances of politically motivated violence highlights the need for effective peace-building strategies that address the practical realities within African communities (Lamidi, 2021). While progress has been made in disaster risk reduction and the celebration of democratic elections in many African states, the continent remains conflict-prone, necessitating proactive measures for conflict prevention and resolution (Niekerk & Coetzee, 2012; Rein, 2015).

Traditional methods of conflict resolution and early warning systems often fall short of providing timely and accurate predictions of political instability, thus stressing the need for innovative approaches that exploit the capabilities of the Fourth Industrial Revolution (4IR) technologies (Muggah & Whitlock, 2022). The AU's role in conflict resolution is central, especially through its Peace and Security Council, which addresses terrorism, peacekeeping missions, and negotiations between conflicting parties (Birhan, 2024). The AU's Peace and Security Council's mandate includes preventative diplomacy, conflict prevention, and peace support operations, signifying the AU's commitment to proactive intervention (Adekera, 2020).

This paper proposes a novel early warning framework that utilises a Random Forest classifier to predict coups in real-time, facilitating the AU's proactive response to emerging threats and safeguarding democratic institutions. Traditional early warning systems often rely on lagging indicators and subjective assessments, limiting their ability to provide timely and accurate predictions of political instability and coups (Sudduth, 2017). Existing literature on coup prediction often focuses on identifying static risk factors and lacks the capacity for real-time monitoring and dynamic risk assessments(Albrecht, 2014; Ward & Beger, 2017; Qiao et al., 2017; Gassebner et al., 2016). Several studies rely on traditional statistical methods and struggle to capture the interactions between the various factors that contribute to coups. While there have been advances in technologies such as machine learning and data analytics, these have not been fully exploited in coup prediction, particularly in the African context. This paper argues that the AU needs a more proactive and data-driven approach that can identify and mitigate coup risks, leveraging the capabilities of the Fourth Industrial Revolution (4IR) technologies to augment its early warning and response mechanisms. The AU's Agenda 2063 emphasises the importance of exploiting technology to improve governance, promote sustainable development, and ensure peace and security. The absence of comprehensive real-time data analysis and predictive modelling capabilities deters the AU's ability to proactively address emerging threats and prevent political instability.

This paper demonstrates how a Random Forest classifier can be developed to create an effective early warning framework, identify the most relevant indicators for predicting coup risk, and address the challenges and opportunities associated with implementing such a framework in the African context. The paper addresses the following specific questions:

- How can 4IR technologies be effectively integrated into an early warning framework to predict coups in real-time?
- What socio-political and economic indicators are most predictive of coup risk in the African context?
- What are the key challenges and opportunities associated with the implementation of a 4IR-based early warning framework for coup prevention in Africa?

The methodology combines a comprehensive literature review with quantitative modelling using a Random Forest classifier to predict coups in African Union states. The review identified key socio-political, economic, social, security, and regional indicators from existing studies as crucial. Quantitative data were collected and pre-processed from sources including The Global Database of Activities, Voice, and Tone (GDELT), World Bank, and development reports. The Random Forest algorithm was chosen for its capacity to manage high-dimensional, non-linear data and its robustness to missing values. The model performance was validated using precision, recall, F1-score, and AUC-ROC metrics. Qualitative insights helped interpret feature importance, contextualise outputs, and refine the predictive framework.

Comparative analysis of predictive models for coup risk in Africa

Modern coup prediction models in Africa incorporate a broad spectrum of socio-political and economic indicators that capture the multi-layered nature of regime stability and risk. Among the most widely used are governance indicators, which include components such as voice and accountability, political stability, government effectiveness, regulatory quality, the rule of law, and the control of corruption (Fosu, 2002; Musumba et al., 2021). These governance dimensions offer insights into the institutional environments within which political power operates and where coups may arise (Ferreira et al., 2023). The levels of political inclusion, freedom of expression, and autonomy of security institutions are also key in assessing susceptibility to military intervention (Kaufmann et al., 2005).

Ethnic composition and political exclusion often serve as key socio-political variables, as ethnic fractionalisation and exclusionary practices have been shown to correlate with higher risks of instability and violent interventions (Klaas, 2019). Economic factors, such as GDP growth or contraction, inflation rates, commodity price shocks, and resource wealth, are integrated as economic indicators. These capture fiscal health and grievances that may motivate or inhibit military actions against civilian governments (Kaufmann, 2003).

Importantly, there is a growing emphasis on combining objective indicators with subjective perception-based data, reflecting political realities as experienced and assessed by domestic and international observers. The integration of ethnic power relations, patronage networks, and coalition sizes further enriches the predictive capacity of models by highlighting social cleavages and political strategies that influence regime durability (Basak, 2024). Overall, these indicators constitute a multi-dimensional framework that aims to capture the intricacy involved in coup risk forecasting. Table 1 summarises the models, key features, and sources of available coup prediction models in Africa.

Table 1. Comparative analysis of predictive models for coup risk in Africa: Socio-political and economic indicators

Model/Approach	Key features	Source
Structural and institutional	Focuses on ethnic competition, military centrality, and political institutionalisation	(Jenkins & Kposowa, 1992) (Kposowa & Jenkins, 1993) (Johnson et al., 1983) (Kanchanasuwon, 1988)
Economic factors	Emphasises economic development, dependency, policy change, and asset specificity	(Collier & Hoeffler, 2005) (O'Kane, 1993) (Hiroi & Omori, 2015) (Hiroi & Omori, 2014) (Korotayev et al., 2018)
Machine learning	Utilises supervised classification algorithms and BRT for conflict prediction	(Musumba et al., 2021) (Xie et al., 2023) (Hoch et al., 2021) (Hoch et al., n.d.)
Climate change	Examines the impact of climate shocks on conflict risk	(Burke et al., 2024) ("The Climate Change and Conflict Nexus in West Africa: A New Approach for Operationally Relevant Vulnerability Assessments", 2023)
Integrated models	Combines socio-political, economic, and climate factors for a comprehensive assessment	(Xie et al., 2023) (Korotayev et al., 2023) (Hoch et al., 2021) (Hoch et al., n.d.)

Structural and institutional indicators in coup prediction

Aggregate governance indicators as predictors

One of the most robust and widely employed tools in coup risk prediction has been the governance indicators developed by Kaufmann et al (2005). These comprise six key dimensions: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, the rule of law, and control of corruption. Together, these indicators offer an aggregate picture of governance quality and state capacity that correlates strongly with political stability. The data from 1996 to 2004 across

209 countries, including African states, demonstrate that improvements in governance are generally associated with decreasing risks of coups and other forms of political violence (Kaufmann, 2005).

Empirical analysis highlights that countries with weak governance indicators or downward governance trends have elevated coup risks. For example, those exhibiting poor rule of law and high corruption often suffer from deteriorating legitimacy and effectiveness, creating openings for military actors to intervene. Given the granularity of governance data, margin-of-error estimates, and statistical significance frameworks included in these indicators, analysts can differentiate between transient fluctuations and persistent governance failures, allowing for tailored preventive policy responses (Kaufmann, 2003).

Role of institutional strength and political inclusion

Political exclusion is an important factor in assessing coup risk. States characterised by narrow ruling coalitions or institutionalised patronage systems tend to face heightened instability risks, largely due to the alienation of other social and political groups. Political exclusion blocks broader coalition-building, raising grievances that may manifest as elite defections or military dissatisfaction. In Côte d'Ivoire, for example, debates over who is included in legitimate politics ignited civil wars and coup attempts, illustrating the destabilising potential of exclusionary practices (Klaas, 2019).

Time-series cross-sectional data from 40 African countries show that governments often extend the tenure of leaders by expanding ruling coalitions through ministerial appointments. This mechanism lowers the likelihood of coup attempts more effectively than modest economic growth increments, highlighting the political utility of inclusiveness as a stability-enhancing tactic (Arriola, 2009). However, this coalition expansion must be carefully balanced, as excessive patronage can undermine state capacity and breed corruption.

Economic indicators and their influence on coup risk

Macroeconomic stability and coup likelihood

Macroeconomic stability plays a central role in reducing the likelihood of coups by mitigating socioeconomic grievances that may motivate military elites or political opponents to seize power (Fosu, 2002). Indicators such as steady GDP growth and low inflation contribute to political stability, whereas economic shocks and downturns increase coup risk

Notably, economic growth alone does not guarantee coup prevention, especially when economic benefits fail to reach broad populations, or when political exclusion persists. Cases where economic contraction occurs alongside effective political inclusion sometimes record lower coup risks, indicating the multi-dimensional nature of the influence of the political economy on coup propensity (Arriola, 2009). This variability underlines the need to integrate multiple economic and political indicators into predictive frameworks.

Resource dependence and economic grievances

Many African countries rely heavily on natural resource wealth; however, the mismanagement of these resources often exacerbates instability. The resource curse framework suggests that countries rich in natural resources tend to exhibit weaker institutions and higher corruption, undermining governance and fomenting discontent (Basak, 2024). Corruption affects public service delivery, erodes the rule of law, and deepens economic inequality, all of which can heighten coup risk by alienating segments of society and weakening regime legitimacy.

African regimes confronted with resource wealth challenges may also become more vulnerable if resource revenues fuel patronage networks and weaken formal state institutions. The combination of economic grievances stemming from poor resource management and institutional decay provides fertile ground for military actors to rationalise intervention, often by claiming to restore order or equitable governance (Bazzi, 2014).

Socio-economic inequality and exclusion

Socio-economic disparities considerably influence political instability and coup risk by intensifying grievances among marginalised groups or elites. High levels of unemployment and poverty create fertile conditions for discontent, affecting both civilian populations and military personnel, who may be compelled to act when economic conditions deteriorate (Olubunmi, 2024). This factor has been reinforced in several African countries, where economic exclusion overlaps with ethnic or regional cleavages, producing compounded vulnerabilities.

Ethnic and social cleavages in coup prediction models

Ethnicity and military loyalty

Identity in the form of ethnicity, to some extent, plays a central role in shaping military loyalty and the risk of coups in Africa. Ethnic composition has been seen to affect group cohesion within the armed forces in some African countries and can either stabilise or destabilise regimes, depending on how leaders manage ethnic representation (Rusell, 2015; Harkness, 2016). Attempts by leaders to manipulate ethnic groups within security institutions often provoke resistance and may lead to violent confrontations, especially when ethnic favouritism undermines meritocratic military professionalism (Harkness, 2014).

Case studies reveal that sudden efforts to restructure ethnically mixed militaries or dismantle established ethnic power bases within the security sector can intensify coup risks by alienating powerful military officers tied to ethnic constituencies (Cederman, 2009). Therefore, the ethnic dimension is an important variable for predicting the likelihood of a coup.

Political exclusion of ethnic groups

Exclusionary political practices that marginalise specific ethnic groups increase the probability of rebellions and coups. Political systems that restrict access to power based on ethnicity can intensify grievances and generate mobilisation against incumbent regimes (Huber, 2017; Lindemann, 2011). The Ethnic Power Relations dataset provides a valuable tool for analysing these factors, showing how excluded groups with sufficient mobilisational capacity and prior experience in conflict are more likely to engage in political violence (Cederman, 2009).

Machine learning applications in political risk

Machine learning (ML) has recently become a transformative tool in political risk assessment and conflict prediction because of its capacity to handle large-scale, multi-dimensional datasets and establish composite non-linear relationships. Compared with traditional econometric or statistical models, ML algorithms improve predictive accuracy by focusing on advanced pattern recognition and variable-interaction detection (Musumba et al., 2017; Beger et al., 2021). These capabilities are particularly valuable when analysing heterogeneous socio-political phenomena such as coups, which typically emerge from the interplay of numerous factors, including governance fragility, economic instability, social unrest, and security conditions.

Several approaches have been explored, ranging from logistic regression and support vector machines (SVMs) to ensemble methods, such as Random Forests and Gradient Boosting. Notably, ensemble learning methods offer robustness and reduce overfitting, making them well-suited for volatile political data (Olabanjo et al., 2021). Nonetheless, applying ML to political events is challenging because of data sparsity, measurement errors, and the rarity of coup events, which complicate model training and evaluation. Furthermore, changes in political regimes and shifts in underlying structural relationships introduce concept drift, which requires adaptive learning frameworks (Bazzi, 2019).

In recent years, efforts have been made to incorporate multi-source data, including social media analytics, economic indicators, and military reports, to deepen feature sets and improve contextual grounding, thereby reinforcing predictive power (Sandhu, 2019). These advancements illustrate the potential of ML to contribute actionable foresight to political stability assessments and early warning systems, despite the inherent difficulties in forecasting sudden events.

Conceptual model of coup prediction

The proposed coup prediction model integrates insights from political science, conflict studies, and machine learning to identify the key factors and mechanisms driving coups in Africa. The model draws on theories of state fragility, political instability, and elite competition to explain the underlying causes of coups and incorporates a range of variables, including political, economic, social, and security indicators to predict coup events. The framework considers domestic factors such as political institutions, economic conditions, and social divisions, as well as external influences such as regional dynamics and international interventions.

Random Forest as a predictive tool for coup prediction in Africa

Random Forest is a machine learning algorithm that uses multiple decision trees to make better predictions. Each tree examines different random parts of the data, and their results are combined by voting for classification or averaging for regression. This ensemble approach makes Random Forest suitable for political instability prediction, where multiple interconnected factors contribute to coup risk.

Theoretical foundations and methodological advantages

Random forest is a commonly used machine learning algorithm that combines the outputs of multiple decision trees to obtain a single result. The strength of the algorithm lies in its ensemble nature, which reduces overfitting and improves generalisation compared to individual decision trees (Mohana et al., 2021). The random forest method can build prediction models using random forest regression trees, which are usually unpruned to provide strong predictions. The bootstrap sampling method is used on regression trees because of its high accuracy.

He et al. (2018) cite characteristics of the Random Forest algorithm that offer several advantages that make it particularly well-suited for predicting coups in African contexts.

1. Handling high-dimensional data: The random forest technique can handle big data with numerous variables in the thousands. It can automatically balance datasets when a class is less frequent than the other classes in the data. This capability is crucial for coup prediction, in which analysts must consider multiple political, economic, social, and security variables simultaneously.
2. Feature importance assessment: Random forests present estimates of variable importance, that is, neural nets. They also offer a superior method for handling missing data. This feature allows researchers to identify the most critical risk factors for coups, thereby enabling more targeted early warning systems.
3. Robustness to outliers: The ensemble nature of Random Forest makes it robust to outliers and noise in the data, which is

particularly important when dealing with political data that may contain measurement errors or extreme values.

4. Non-parametric nature: Unlike traditional statistical models, Random Forest does not require assumptions about data distribution, making it suitable for complex political phenomena where relationships may be non-linear.

Data requirements and feature engineering for coup prediction
Multi-dimensional data sources

Effective coup prediction using Random Forest requires comprehensive data collection across multiple dimensions. The Global Database of Activities, Voice, and Tone (GDELT Project) records broadcast, print, and web news in over 100 languages every second of every day, identifying people, locations, organisations, counts, themes, outlets, and events that propel our global community (Scornet, 2023; Zebrowski, 2024). These data sources provide the rich, multi-dimensional input required for Random Forest algorithms. Based on the literature and empirical evidence reviewed above, the key feature categories for coup prediction in Africa include political, economic, social, security, and military, and international relations variables.

Implementation framework

The implementation of Random Forest for coup prediction in Africa requires a systematic approach to data collection and pre-processing. Using Random Forest methodology, analysts can analyse survey and climate data from second-order political boundaries to explore what predicts various phenomena. This includes the different dimensions of beliefs and perceptions that may influence political stability.

Studies have shown the superior performance of random forests in political prediction tasks. Random forest achieved impressive results with a precision score of 0.835, an accuracy score of 0.804, and an AUC score of 0.942 in predictive modelling tasks (Whetten et al., 2021; Jorquera, 2023). These performance metrics demonstrate the algorithm's reliability for high-stakes prediction tasks, such as coup forecasting. Among various ML techniques, Random Forest has performed well in early warning systems with 96.06% accuracy and 98.6% precision. This level of performance makes it particularly suitable for deployment in real-world early warning systems.

Tests have shown that creating a prediction model with modern methods, such as Random Forest and XGBoost, increases the accuracy of the prediction from 70% to approximately 80% compared to the standard logit model (Ji, 2023). This significant improvement in predictive accuracy demonstrates the value of machine learning approaches compared to traditional statistical methods.

While artificial neural networks (ANN) achieved a maximum prediction accuracy of 85% with a precision of 82%, surpassing logistic regression, support vector machines, and random forests in some contexts (Ikumariegbe, 2024), random forests remain advantageous because of their interpretability and lower computational requirements.

Case study: Guinea coup prediction framework

Background and Context

The September 2021 military coup in Guinea provides an excellent case study for demonstrating how Random Forest could have been employed for early warning. The coup, led by Colonel Mamady Doumbouya, resulted in the overthrow of President Alpha Condé, who had been in power since 2010.

Pre-coup indicators and data features

Based on the Random Forest framework, several key indicators were relevant for predicting the Guinea coup.

Table 2. Political indicators

Factor	Description	Impact Level	Data Source
Constitutional Violations	Condé's third term obtained after a much-contested constitutional amendment, violating the constitutional limitation of presidential competence to only two terms	Very High	Electoral data, Constitutional records
Electoral Fraud	Results of October 18, 2020 presidential elections where Condé won for the third time, obtaining 59.5% of the votes (the	High	Election monitoring reports

	results could be falsified)		
Authoritarian Governance	Under Condé, the administration yielded disappointing economic results and he was increasingly perceived as an authoritarian ruler who handled his opponents and critics with harsh repressiveness	High	Freedom House reports
Political Protests	Electoral campaign took place with active protests against Condé's candidature because this was violating the constitutional limitation	High	Event data (GDELT)
Referendum Manipulation	Officials organized a referendum where 91.6% of participants agreed to constitutional amendments to prolong the presidential term to 6 years	High	Official voting records

Table 3. Economic factors

Factor	Description	Impact Level	Data Source
GDP Growth Paradox	GDP growth in the pre-COVID period was at 6% per year, but the IMF characterised the situation in 2019 as "growth without development"	High	World Bank, IMF data
Sectoral Imbalance	Success in the mining industry in the sacrifice of other sectors	Medium	Economic sector data
Food Price Inflation	In January 2021, prices on imported flour, grains and sugar raised, government raised bread prices from 1500 to 2000 Guinean francs, triggering a wave of protests	Very High	Consumer price indices
Fuel Price Increases	One month before the coup, a raise of gasoline price from 9 to 11 thousand Guinean francs per litre was announced	High	Energy price data
Economic Mismanagement	Economic mismanagement consisting of political corruption and a lack of effective development policies	High	Corruption indices

Table 4. Social variables

Factor	Description	Impact Level	Data Source
Ethnic Marginalisation	Members from the Malinké ethnic group have remained in political authority since Guinea's independence in 1959, while Fulanis, who are the majority population, have continued to face social and economic marginalisation	High	Demographic data, Ethnic composition
Bread Riots	Bread riots and other conflicts continued during the first half of 2021	High	Social unrest data
Popular Dissatisfaction	At the moment of the coup, the situation in the country was so unstable that many Guineans could suggest the intervention of the army as a solution to many problems	Very High	Public opinion surveys
COVID-19 Impact	With the beginning of COVID-19 they became more and more forgotten	Medium	Health and economic data

Table 5. Security indicators

Factor	Description	Impact Level	Data Source
Military Budget Cuts	The government increased financing for Parliament and presidential services while cutting resources for the army and police, leading to lower soldiers' and officers' revenues	Very High	Defense budget data
Unit Resource Constraints	These circumstances, in the context of cuts to the military budget (Doumbouya complained many times that his unit lacked resources), could be possible reasons for the coup	Very High	Military unit reports
Elite Military Unit	Specially trained - mostly abroad - military group, composed of barely 100 persons, but able to confront the regular army	High	Military organizational data
Military-Government Tensions	Tension between Doumbouya and the minister of defense, Mohamed Diane, which transferred the special task group from the capital to Forecariah's base	High	Military intelligence reports

Table 6. Regional factors

Factor	Description	Impact Level	Data Source
Regional Coup Contagion	Guinea was the third West African country to experience a violent transfer in a six-month period. In April, Chad's president Idriss Déby was killed and replaced by his son, and in May, Mali saw its second coup in nine months	High	Regional conflict databases
Neighboring Instability	The present Guinean military coup will likely encourage military personnel or militias in unstable neighboring countries, such as Guinea-Bissau, Mali, and Chad, to act against their own governments	Medium	Regional stability indices
Economic Isolation	Impact of regional economic sanctions and isolation	Medium	Trade data, ECOWAS records

Figure 1 illustrates how the Random Forest processes these indicators.

Figure 1. Guinea Coup Prediction Framework Using Random Forest

Input data sources

├── Political indicators

│ ├── Democratic governance index

│ ├── Political grievances score

│ ├── Constitutional crisis index

│ └── Civil society activity level

├── Economic indicators

│ ├── GDP growth rate

│ ├── Inflation rate

```
│   ├── Youth unemployment rate
│   └── Corruption perception index
├── Social indicators
│   ├── Protest frequency
│   ├── Ethnic tension index
│   ├── Social media sentiment
│   └── Regional inequality measure
└── Security indicators
    ├── Military satisfaction index
    ├── Defence spending ratio
    ├── Previous coup attempts
    └── Regional instability score
```

Random Forest processing

```
├── Tree 1: Political + economic features
├── Tree 2: Social + security features
├── Tree 3: Economic + security features
├── Tree n: Random feature combinations
└── Ensemble voting
```

Output

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├── Coup risk probability (0-1)
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├── Feature importance rankings

├── Confidence intervals

└── Alert thresholds

Predictive timeline and early warning

In the case of Guinea, the Random Forest model would have likely identified elevated coup risk beginning in 2020 with the constitutional crisis, with risk levels increasing through 2021 as economic and social indicators deteriorated. The model would have provided a 3-6-month early warning based on constitutional changes and political unrest. 1-3 months' critical alert as economic conditions worsened and military dissatisfaction grew. An immediate risk assessment in the weeks leading up to the coup, as multiple indicators converged.

Performance metrics and validation

For the Guinea case, the Random Forest model's performance could be evaluated using:

Precision: Ability to correctly identify coup risk without false alarms

Recall: Capacity to detect actual coup attempts

F1-Score: Balanced measure of precision and recall

AUC-ROC: Overall discriminative ability

Limitations and considerations

The success of Random Forest in coup prediction depends on several factors, namely high-quality, comprehensive data collection; appropriate feature engineering; robust model validation; and continuous refinement based on new developments. As demonstrated through the Guinea case study, the algorithm can provide valuable early warning capabilities when it is properly implemented and integrated with existing conflict prevention mechanisms.

A central challenge in coup prediction is the inconsistent quality and coverage of the disparate data sources. Social media data, for example, may be sparse or unrepresentative in less connected or censored regions. Military data may be classified or unreliable because of political sensitivities (Reiter, 2020). Political reporting is subject to bias and incomplete coverage. These limitations constrain the accuracy and generalisability of the model (Bazzi, 2019). Spatial and temporal data resolution gaps reduce the granularity of detection. Addressing these constraints involves triangulation across multiple data streams, rigorous data provenance assessment, and cautious interpretation of model outputs.

While Random Forests and similar methods have demonstrated their ability to detect persistent patterns of instability, predicting previously unseen or sudden coup onset remains inherently challenging (Wang et al., 2016). Models rely heavily on historical patterns and struggle with novelty, reducing early warning capacities for first-time or escalating events. This limitation reflects the non-stationary, composite nature of political factors and suggests that quantitative models should be complemented by qualitative intelligence, expert judgment, and scenario-based planning to enhance the detection of new outbreaks (Bazzi, 2019).

The deployment of coup prediction models carries significant ethical and political risks. False positives can provoke tension, unwarranted interventions, or political blame. Conversely, missed predictions can endanger civilian lives and political stability (Okon, 2022). Ensuring transparency regarding model limitations, maintaining rigorous validation, and complementing algorithmic outputs with human oversight are essential for navigating these risks. Furthermore, respecting sovereignty, avoiding stigmatisation, and ensuring accountability are integral to responsible use (Bazzi, 2019).

Human oversight is imperative in the application of Random Forest modelling in any context, in this case, for coup detection and prevention. Although the model offers significant capabilities for monitoring and predicting political instability, it is not infallible. Algorithms can inadvertently perpetuate biases, leading to misinterpretations of data and the unjust targeting of specific communities (Smith, 2021). Human oversight ensures that ethical considerations, context, and an understanding of socio-political factors are integrated into decision-making processes.

Moreover, human involvement promotes accountability and transparency, which are essential for maintaining public trust in the AU's interventions. By having skilled personnel review and validate the outputs generated by such novel approaches, the risks associated with algorithmic bias can be mitigated and ensure that interventions are fair and just. Additionally, human oversight facilitates adaptability in response strategies, allowing for considerations of local contexts and engagement with civil society for comprehensive insights. This collaborative approach augments the effectiveness of preventative measures against coups, ensuring that technology empowers communities rather than marginalises them.

Future research should focus on improving data quality and availability, developing standardised evaluation metrics, and creating more sophisticated ensemble approaches that combine Random Forest with other machine learning techniques. The integration of 4IR technologies offers unprecedented opportunities to enhance the speed, accuracy, and accessibility of coup prediction systems, potentially saving lives and preventing political instability across Africa.

The implementation of Random Forest-based early warning systems requires close collaboration between researchers, policymakers, and technology developers to ensure that these powerful tools are deployed responsibly and effectively in the service of peace and stability. As the field continues to evolve, Random Forest is potentially a cornerstone technology in the broader toolkit of conflict prediction and prevention methodologies.

Conclusion

The proposed 4IR-based early warning framework employing Random Forest machine learning offers a significant advancement in predicting coup events within African Union states. The system integrates multi-dimensional socio-political and economic indicators alongside security and regional factors, which enables timely dynamic risk assessments that surpass traditional methods reliant on static or lagging data. The case study of Guinea's 2021 coup exemplifies the model's capacity to provide actionable early warnings, potentially allowing the AU and stakeholders to intervene proactively, thereby enhancing political stability and governance in the region.

However, the success of the model hinges on overcoming challenges such as inconsistent data quality, incomplete coverage, and the convolution of political instability. Ethical considerations necessitate human oversight to mitigate bias and ensure locally informed and accountable decision-making. The AU's commitment to Agenda 2063 underlines the critical value of leveraging technology to support peace and security initiatives.

Future research should focus on improving data integration, exploring ensemble learning fusion with other algorithms, and refining the evaluation metrics to further enhance the predictive power. The proposed framework illustrates how 4IR technologies can transform political risk forecasting and conflict prevention, paving the way for more resilient African democratic institutions and more effective, technology-driven peace-building efforts.

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References

Adekera, D. (2020). African Union – United Nations Hybrid Operation in Darfur (UNAMID): A New Template for Future Peacekeeping Operations? The International Journal of Humanities & Social Studies, 8(7). https://doi.org/10.24940/theijhss/2020/v8/i7/hs2007-096

Albrecht, H. (2014). The Myth of Coup-proofing. *Armed Forces & Society*, *41*(4), 659–687. https://doi.org/10.1177/0095327x14544518

Arriola, L. R. (2009). Patronage and political stability in Africa. SAGE Publishing. https://doi.org/10.1177/0010414009332126

Basak, B. (2024). Analysing the impact of corruption for underdevelopment in African countries. International Journal for Multidisciplinary Research. https://doi.org/10.36948/ijfmr.2024.v06i02.18255

Bazzi, S. & Blattman, C. (2014). Economic shocks and conflict: Evidence from commodity prices. American Economic Association. https://doi.org/10.1257/mac.6.4.1

Bazzi, S., Blair, R., Blattman, C., Dube, O., Gudgeon, M., & Peck, R. M. (2019). The promise and pitfalls of conflict prediction: Evidence from Colombia and Indonesia. None. https://doi.org/10.3386/w25980

Beger, A., Morgan, R. K., Ward, M. D., & Ward, M. D. (2021). Reassessing the Role of Theory and Machine Learning in Forecasting Civil Conflict. Journal of Conflict Resolution. https://doi.org/10.1177/0022002720982358

Birhan, A. T. (2024). The African Union and Conflict Resolution: Challenges and Prospects. Social Science and Humanities Journal, 8(3), 34576. https://doi.org/10.18535/sshj.v8i03.958

Brandt, P. T., & Ulfelder, J. (2011). Economic Growth and Political Instability. Social Science Research Network. https://doi.org/10.2139/SSRN.1907643

Cederman, L., Wimmer, A., & Min, B. (2009). Why do ethnic groups rebel? new data and analysis. Cambridge University Press. https://doi.org/10.1017/s0043887109990219

Eizenga, D. (2022). Peacebuilding and democracy in Africa. In Routledge eBooks (pp. 155–168). https://doi.org/10.4324/9780429060038-14

Ferreira, J. J., Gomes, S., Lopes, J. M., & Zhang, J. Z. (2023). Ticking time bombs: The MENA and SSA regions' geopolitical risks. *Resources Policy*, *85*, 103938. https://doi.org/10.1016/j.resourpol.2023.103938

Fosu, A. K. (2002). Political instability and economic growth: Implications of coup events in Sub-Saharan Africa. The American Journal of Economics and Sociology. https://doi.org/10.1111/1536-7150.00162

Gassebner, M., Gutmann, J., & Voigt, S. (2016). When to expect a coup d'état? An extreme bounds analysis of coup determinants. *Public Choice*, *169*(3–4), 293–313. https://doi.org/10.1007/s11127-016-0365-0

Harkness, K. A. (2014). The ethnic army and the state. SAGE Publishing. https://doi.org/10.1177/0022002714545332

Harkness, K. A. (2016). The Ethnic Army and the State Explaining Coup Traps and the Difficulties of Democratization in Africa. Journal of Conflict Resolution. https://doi.org/10.1177/0022002714545332

He, L., Levine, R. A., Fan, J., Beemer, J., & Stronach, J. (2018). Random Forest as a Predictive Analytics Alternative to Regression in Institutional Research. Practical Assessment, Research and Evaluation. https://doi.org/10.7275/1WPR-M024

Huber, J. D. (2017). Exclusion by elections: Inequality, ethnic identity, and democracy.

https://openlibrary.org/books/OL26351315M/Exclusion_by_elections

Ikumariegbe, O. V., Okwuise,, Y, U., Micah, E. E. M., Muhammad, A., Ibrahim, B. M., Jeroh, E., Aliu, J., & Jeroh, E. (2024). Fitting machine learning models for the identification of social vulnerability in the event of political instability in Nigeria. International Journal of Religion. https://doi.org/10.61707/3dwt0k35

Ji, C. (2023, April 28). Research on an integrated index prediction model based on RF-XGBOOST-ANN. https://doi.org/10.1109/ICCECT57938.2023.10140383

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2003). Governance Matters III: Governance Indicators for 1996–2002. In World Bank policy research working paper. https://doi.org/10.1596/1813-9450-3106

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2005). Governance Matters IV: Governance Indicators for 1996-2004. In World Bank policy research working paper. https://doi.org/10.1596/1813-9450-3630

Klaas, B. (2019). Political Exclusion in Africa. Oxford Research Encyclopedia of Politics. Retrieved 11 June 2025, from https://oxfordre.com/politics/view/10.1093/acrefore/9780190228637.001.0001/acrefore-9780190228637-e-1326.

Lamidi, K. O. (2021). An Evaluation of Peace Building Strategies in Southwestern Nigeria: Quantitative and Qualitative Examples. Journal of African Conflicts and Peace Studies, 4(2). https://doi.org/10.5038/2325-484x.4.2.1143

Lindemann, S. (2011). The Ethnic Politics of Coup Avoidance: Evidence from Zambia and Uganda. Africa Spectrum. https://doi.org/10.1177/000203971104600201

Mohana, R., Kumar Reddy, C. K., Anisha, P. R., & Murthy, B. V. R. (2021). Random forest algorithms for the classification of tree-based ensemble. Materials Today: Proceedings. https://doi.org/10.1016/J.MATPR.2021.01.788

Muggah, R., & Whitlock, M. A. (2022). Reflections on the Evolution of Conflict Early Warning. Stability: International Journal of Security and Development. https://doi.org/10.5334/sta.857

Musumba, M., Fatema, N., & Kibriya, S. (2021). Prevention Is Better Than Cure: Machine Learning Approach to Conflict Prediction in Sub-Saharan Africa. Sustainability. https://doi.org/10.3390/SU13137366

Niekerk, D. van, & Coetzee, C. (2012). Chapter 17 African Experiences in Community-Based Disaster Risk Reduction. In Community, environment and disaster risk management (p. 333). Emerald Publishing Limited. https://doi.org/10.1108/s2040-7262(2012)0000010023

O'Kane, R. H. T. (1993). Coups d'État in Africa: A Political Economy Approach. Journal of Peace Research. https://doi.org/10.1177/0022343393030003002

Okon, E. N. (2022). Why military coups are back in Africa. Revista Brasileira de Estudos Africanos. https://doi.org/10.22456/2448-3923.123042

Olabanjo, O. A., Olabanjo, O. A., Aribisala, B. S., Aribisala, B. S., Mazzara, M., & Wusu, A. S. (2021). An ensemble machine learning model for the prediction of danger zones: Towards a global counter-terrorism. https://doi.org/10.1016/J.SOCL.2021.100020

Olubunmi, A., Solomon, A., Ayantayo Ojo, & Kugbayi, O. (2024). The fragility of democracy in Africa: Are military coups a never-ending issue? PanAfrican Journal of Governance and Development. https://doi.org/10.46404/panjogov.v5i2.5703

Qiao, F., Li, P., Wang, H., Ding, Z., Zhang, X., & Cheng, J. (2017). Predicting Social Unrest Events with Hidden Markov Models Using GDELT. *Discrete Dynamics in Nature and Society*, *2017*, 1–13. https://doi.org/10.1155/2017/8180272

Rein, C. (2015). Enhancing Peace and Security in Africa through Institutional Cooperation. Contemporary Security Policy, 36(2), 267. https://doi.org/10.1080/13523260.2015.1061757

Reiter, D. (2020). Avoiding the Coup-Proofing Dilemma: Consolidating Political Control While Maximizing Military Power. Foreign Policy Analysis. https://doi.org/10.1093/FPA/ORAA001

Russell, S. (2015). The ties that bind: Sub-state identity and African militaries. African Security Review, 24(3), 324–331. https://doi.org/10.1080/10246029.2015.1066261

Sandhu, M. (2019). From social media to expert reports: automatically validating and extending complex conceptual models using machine learning approaches. https://knowledgecommons.lakeheadu.ca/handle/2453/4346

Scornet, E. (2023). Trees, forests, and impurity-based variable importance in regression. Annales de l'I.H.P. https://doi.org/10.1214/21-aihp1240

Sudduth, J. K. (2017). Coup risk, coup-proofing and leader survival. *Journal of Peace Research*, *54*(1), 3–15. https://doi.org/10.1177/0022343316676885

Wang, H., Wang, H., Yang, F., & Luo, Z. (2016). An experimental study of the intrinsic stability of random forest variable importance measures. BMC Bioinformatics. https://doi.org/10.1186/S12859-016-0900-5

Ward, M. D., & Beger, A. (2017). Lessons from near real-time forecasting of irregular leadership changes. *Journal of Peace Research*, *54*(2), 141–156. https://doi.org/10.1177/0022343316680858

Whetten, A. B., Whetten, A. B., Stevens, J. R., & Cann, D. M. (2021). The implementation of random survival forests in conflict management data: An examination of power sharing and third party mediation in post-conflict countries. PLOS ONE. https://doi.org/10.1371/JOURNAL.PONE.0250963

Zebrowski, A. & Afli, H. (2024). Predicting country instability using Bayesian deep learning and random forest. arXiv.org. https://doi.org/10.48550/arXiv.2411.06639