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Prediction of Political Instability by Using Pre-Trained Neural Networks

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This research aims to enhance and optimize the decision-making process in the political science domain by exploring the potential of machine learning. The aim was to create a pre-trained neural network to predict the political instability in any country (a prediction that aids decision-makers in handling government affairs and crisis prevention). We constructed four pre-trained neural networks, each tailored to a specific indicator (Human Development Index, Currency Strength Index, Tax to GDP Ratio, and Fragile States Index). These indicators are selected based on their strong correlation and how their concurrent performance impacts the political landscape of any country. The neural networks exhibited exceptional performance, achieving accuracy rates above 85%. The model built on the FSI demonstrated an astonishing accuracy of 99.67%, underscoring its potential for comprehensive assessments. The prospect envisions amalgamating the outputs of these pre-trained neural networks into a unified, deep-learning network, poised to yield collective decisions and recommend policy initiatives.

Keywords: Political instability prediction, Machine Learning, decision-making process, neural networks, data analysis.

Introduction:

Political stability stands as a linchpin for thriving societies, fostering conducive environments for economic growth, social progress, and overall well-being [1][2]. In today's dynamic global landscape, accurately assessing and predicting political stability holds paramount significance amidst geopolitical shifts and socio-economic fluctuations. Instances of political instability, arising from various internal and external pressures, possess ripple effects that transcend national borders [3]. Recent strides in advanced computational techniques, notably neural networks, present a promising avenue for predictive analysis across diverse domains [4][5]. Leveraging these capabilities, this study aims to harness neural networks to address the critical issue of political stability, paving the way for a novel framework facilitating informed and timely decision-making [6].

In the realm of political risk assessment, studies have highlighted the potential of machine learning (ML) algorithms in predicting instability [3][7]. Machine Learning algorithms are employed to forecast conflict likelihood in sub-Saharan Africa, outperforming traditional statistical methods [3]. Similarly, ML algorithms have been used in the integration of various institutional, economic, and demographic factors to predict civil war onset in Africa [7].

ML algorithms have found applications in supporting decision-making across diverse domains, such as public health, energy, and agriculture [2]. For instance, Machine Learning algorithms have demonstrated considerable utility in formulating policy recommendations for sustainable energy policies [2]. Moreover, referencing Sørensen & and Ansell (2023), the concept of political robustness warrants attention [8]. This concept delves into the resilience and adaptability of political systems, which can be intertwined with this research. By integrating the notion of political robustness, this study aims to enhance predictive models by accounting for the resilience of political structures in the face of potential instabilities, thereby enriching crisis management recommendations.

The detrimental impact of political instability on a nation's fabric, spanning economic, social, and institutional spheres, is unequivocal. Timely prediction of such crises holds the key to preemptive decision-making, averting potential fallout through astute policy formulation and crisis management. However, the crux lies in the need for swift predictions amid vast data inflows, allowing decision-making bodies the critical space to craft effective strategies in response. This research initiative strategically integrates machine learning techniques with the decision-making process to address this inherent challenge. Within organizations, the perpetual trade-off between extensive data influx and the time required to process it hinders the formulation of actionable plans. Analogously, the realm of politics and governance faces a deluge of crucial data with limited human capacity to manage and process it within stringent timeframes. This challenge forms the cornerstone of this research endeavor. The goal is to leverage the potential of machine learning technology to develop pre-trained models capable of processing extensive data beforehand, furnishing decision-makers with concise, pertinent information. These models aim to assist decision-making bodies by synthesizing crucial insights, thereby facilitating the decision-making process and enabling more informed, timely, and effective policymaking in the realm of politics and governance.

By amalgamating the prowess of ML algorithms with the concept of political robustness, this research endeavors to pioneer a holistic approach toward forecasting political instability and facilitating informed decision-making during critical junctures.

Research Problem:

This study seeks to answer the pivotal question: Can neural networks effectively predict political instability in nations based on socio-economic and political indicators?

Political instability in any country is a complex and multi-tiered issue. It is the outcome of multiple factors of different origins reaching a critical bent/breakpoint concurrently. It is crucially important to have a deeper understanding of the intricate correlation of social sciences knowledge, historical facts, and policy-making culture to analyze and comment on the political climate of any country. To create an agent that can assess, analyze, and predict political instability it is indispensable for the agent to be trained in subjective (domain knowledge) and objective data, be able to create relations among different variables, and make predictions accordingly. So far, the work done in this regard has limitations – and much room for more work in it - such as the absence of domain knowledge, selection of fewer or one type of variables, long lead times, and forecasting without meaningful interpretation or policy recommendations – as identified in the literature review. These studies take a lead time of two years which means their focus is other than urgent crisis management.

Moreover, the identified problem is critical in a way that although the contributing factors worsen over time, a single incident sets off a chain of events and throws the entire country into chaos, leaving hardly any time and space for policymakers to deal with the crisis effectively. The proposed model is dedicated to forecasting political instability with a lead time of 6 months to 1 year and makes recommendations accordingly to manage the crisis on an ad-hoc basis. The research problem addresses ad-hoc crisis management because the proposed AI-driven political analyst aims to provide policymakers with the tools and information necessary to make informed decisions in real-time crises. Ad-hoc crisis management refers to the improvisational and reactive nature of crisis management, where decisions must be made quickly and effectively in the face of unpredictable events.

In such situations, having access to accurate, real-time information is crucial for policymakers to make informed decisions. The proposed AI-driven political analyst will provide this information by assessing political uncertainty in a country, identifying the origins of that uncertainty, predicting political instability with a lead time, and providing evidence-based recommendations for policy measures. By addressing ad-hoc crisis management, the proposed study has the potential to significantly improve the ability of policymakers to respond to crises effectively and efficiently, ultimately contributing to the sustainable development of countries.

Novelty Statement:

In a pioneering fusion of machine learning innovation and decision-making acumen, this research introduces a groundbreaking approach to predictive analytics in the realm of political instability. By strategically integrating pre-trained neural networks with a curated set of key performance indicators, the study navigates the perennial trade-off between vast data influx and the imperative for timely, actionable decisions. This novel methodology seeks to empower decision-making bodies by harnessing the potential of machine learning technology to process extensive data in advance, offering a prophetic lens into a nation's socioeconomic and political landscape. As the first of its kind, this research not only addresses the critical challenge of timely crisis prediction but propels the frontier of informed decision-making in governance to unprecedented heights."

Aim:

The study aims to enhance and optimize the decision-making process by tapping the potential of and integrating machine learning with it.

Objectives:

The objective of this research is to investigate the prospects of building a machine learning-based AI Agent:

- To study and probe the domain data and investigate the correlation of selected economic, social, and institutional indicators, a combination of which results in acute political instability in any country.
- To create a Time Series Forecasting with Deep Learning using a combination of various neural network architectures in predicting the political instability in any country.

Literature Review:

Political instability is a multifaceted and complex phenomenon with far-reaching implications for both domestic governance and international relations. Understanding the root causes of political instability is crucial for policymakers, scholars, and practitioners. This literature review provides an overview of existing theories and models related to political instability, with a focus on factors such as economic conditions, social unrest, and historical context.

Ouedraogo et al. (2022): Examines conflict and political instability's impact on banking crises in developing nations [9]. This work comprehensively studies the interconnection between political instability and financial crises in emerging economies. However, it may lack a deeper analysis of specific regional impacts or alternative economic indicators affecting banking stability. It's relevant to your study as it provides insights into the broader repercussions of political instability.

Dalyop (2019): Explores the relationship between political instability and economic growth in Africa [1]. The paper delves into the ramifications of political turbulence on economic advancement in the African context. However, it might benefit from a more extensive comparative analysis across different continents to showcase unique impacts. This work is relevant as it offers insight into the economic consequences of political instability.

Chen et al. (2019): Investigates conflict prediction in sub-Saharan Africa through machine learning algorithms [3]. This study showcases the efficacy of ML algorithms in forecasting conflicts. Yet, it might lack a comprehensive evaluation of the predictive model's robustness under different scenarios. It's relevant to your work as it illustrates the application of machine learning in predicting political instability.

Kull et al. (2020): Present a machine-learning approach for policy recommendations in sustainable energy policies [2]. This work focuses on recommending sustainable energy policies through ML models. However, it might lack a detailed exploration of the policy implementation challenges. It's relevant to your study as it demonstrates machine learning's applicability in policy recommendations.

Baillie et al. (2021): Proposes explainable models for forecasting political instability emergence [4]. This paper focuses on interpretable models to predict political instability. However, it might need further validation on real-time data for robustness. It's relevant as it provides insights into explainable models, aligning with your work on political instability prediction.

IMF Working Papers 2021: The IMF's papers might offer a broader macroeconomic perspective on political instability and its financial implications [10]. However, these papers may lack in-depth analysis and might rely heavily on aggregated data. It's relevant as it provides a macroeconomic viewpoint on political instability.

Chen et al. (2019): Present a deep learning approach for political stability prediction [11]. This paper focuses on leveraging deep learning for stability forecasting. However, it might lack exploration of potential biases in the model. It's relevant as it explores the depth of machine learning in stability prediction.

Bourahla et al. (2019): Explores social unrest forecasting using machine learning [12]. This study concentrates on predicting social unrest using ML techniques. However, it might lack comprehensive coverage of diverse socio-cultural factors impacting unrest. It's relevant as it showcases machine learning's role in forecasting social instability.

Chen et al. (2021): Proposes explainable models for forecasting political instability emergence [13]. This paper focuses on interpretable models for predicting instability. However, it might need further validation for generalizability across diverse regions. It's relevant as it explores explainable models in instability prediction.

Jahani et al. (2022): Introduces conflict forecasting using machine learning [5]. This work centers on forecasting conflicts through ML techniques. However, it might lack an in-depth analysis of the cultural nuances influencing conflicts. It’s relevant as it delves into ML for conflict prediction.

Wang et al. (2023): Focuses on enhancing decision-making in political science using neural network fusion [6]. This paper concentrates on leveraging neural network fusion for decision-making. However, it might benefit from additional exploration of model interpretability. It's relevant for its focus on improving decision-making using neural networks.

An et al. (2019): Discusses oil price predictors using machine learning [14]. This study focuses on predicting oil prices using ML. However, it might need validation across diverse oil market scenarios. It’s relevant due to its exploration of ML in predicting economic factors.

Lima and Delen (2020): Explores predicting and explaining corruption across countries through a machine learning approach [15]. This research concentrates on predicting and explaining corruption using ML. However, it might lack extensive exploration of historical contextual factors in corruption. It’s relevant for its application of ML in understanding corruption.

Hossain et al. (2022): Identifies geopolitical event precursors using attention-based LSTMs [16]. This study focuses on identifying geopolitical event precursors through LSTM models. However, it might need further validation for robustness across various geopolitical contexts. It’s relevant as it employs ML for geopolitical event detection.

D'Orazio and Lin (2022): Discuss forecasting conflict in Africa with automated ML systems [7]. This work centers on conflict prediction in Africa through automated ML. However, it might require more extensive validation for different conflict types and regions. It’s relevant as it applies ML in forecasting conflicts.

Oladele and Ayetiran (2023): Explores social unrest prediction through sentiment analysis on Twitter using a Support Vector Machine [17]. This study focuses on predicting social unrest via sentiment analysis on Twitter. It might need further analysis of how regional language nuances impact sentiment analysis accuracy. It’s relevant for its application of social media analysis in unrest prediction.

Wiesmüller (2023): Discusses relational economics and organization governance concerning artificial intelligence [18]. This paper explores the governance aspect of AI within organizational settings. However, it might benefit from more empirical case studies illustrating the proposed relational governance model. It’s relevant for its focus on AI governance within organizational frameworks.

Donnay (2023): Examines big data for monitoring political instability [19]. This work delves into using big data for monitoring political instability. However, it might lack a comprehensive assessment of data privacy and the ethical implications of using big data for this purpose. It’s relevant for its exploration of big data applications in monitoring instability.

Medvedev et al. (2022): Investigates machine learning for ranking factors of global and regional protest destabilization, focusing on the Afrasian Instability Macrozone [20]. This study concentrates on ranking factors of protest destabilization. It might benefit from more extensive validation across diverse geographical and political contexts. It’s relevant for its focus on ML in assessing protest destabilization factors.

Obukhov and Brovelli (2023): Discusses identifying conditioning factors and predictors of conflict likelihood for machine learning models: A literature review [21]. This work focuses on identifying conditioning factors and predictors for conflict likelihood. It might require further exploration of real-time application challenges for these models. It’s relevant for its exploration of conflict prediction factors.

Datasets:

This research endeavor has meticulously selected indicators that wield a pivotal influence on shaping the political landscape of any given country. These chosen metrics are instrumental in determining the trajectory of a nation's political dynamics, often serving as decisive factors in pivotal junctures. In this study, we have utilized a comprehensive set of cross-country data to assess and analyze the political landscape of various nations. Specifically, we have employed data derived from reputable and publicly accessible sources. These include the Human Development Index data from 1990 to 2022, sourced from the United Nations Development Programme (UNDP). The Fragile State Index data from 2006 to 2023 was sourced from the Fund for Peace, a distinguished non-profit research organization in the United States. The Tax-to-GDP ratio data from 1990 to 2022, extracted from the "Revenue Statistics" report published by the Organisation for Economic Co-operation and Development (OECD). Lastly, the Currency Strength Index data from 1990 to 2022 sourced from international financial institutions.

These meticulously selected datasets collectively serve as a robust foundation for our analytical framework, enabling us to discern critical patterns and dynamics within the political landscapes of the examined countries over the specified periods. The data utilized in our research project is sourced from international governmental organizations, and we have employed datasets available up to the latest years provided by these sources. It is essential to note that these international organizations typically incorporate recent data only when the statistics have stabilized and matured. This cautious standard is to facilitate national and governmental agencies, research institutions, and academicians who rely on accurate and stable data for further processing and analysis. By aligning with these practices, our research ensures the incorporation of reliable and robust information, contributing to the overall credibility and validity of our findings.

Labels and Data Correlation:

Label Human Development Index (HDI):

The first high-risk classifier data was obtained from the Human Development Index. The Human Development Index (HDI) given by the United Nations Development Programme (UNDP) is based on three key dimensions:

- Health: This is assessed using life expectancy at birth. It reflects the average number of years a person is expected to live from birth, considering mortality rates.
- Education: This dimension is evaluated using two indicators:
- Mean Years of Schooling: The average number of years of education received by people aged 25 years or older.
- Expected Years of Schooling: The total years of schooling a child entering school at a given age can expect to receive, assuming prevailing patterns of age-specific enrolment ratios.
- Standard of Living: This is measured by Gross National Income (GNI) per capita, adjusted for purchasing power parity (PPP) to account for cost-of-living differences between countries.

The HDI is a composite index that combines these three dimensions to provide a broader view of human development. It's important to note that the HDI is just one of many measures used to assess and compare human development across countries. Other indices and indicators are also utilized to gain a comprehensive understanding of a nation's development.

- Correlation: Nations with higher HDI scores exhibit stronger political stability. This correlation arises from the fact that countries with robust human development indicators, such as education, healthcare, and income, are more likely to have engaged, informed, and empowered citizenry. These factors contribute to the establishment of stable political institutions and participatory governance structures.

Impact on Political Landscape:

Higher HDI scores foster an environment conducive to democratic practices and good governance. Educated and healthy citizens are more likely to participate in civic activities, which enables the formation of stable political institutions. Additionally, governments in high-HDI countries often have greater capacity to implement policies that address societal needs, which further bolsters political stability.

Label - Fragile State Index (FSI):

The Fragile States Index (FSI) provided by the Fund for Peace is a composite index that assesses and ranks countries based on their level of fragility. It considers multiple social, economic, and political indicators. The key features behind the FSI include:

- Social Indicators:
- Demographic Pressures: Population growth and distribution.
- Refugees and Internally Displaced Persons (IDPs): Displacement due to conflict or other factors.
- Group Grievance: Tensions or conflicts between different social, ethnic, or religious groups.
- Human Flight and Brain Drain: Emigration of skilled individuals.
- Economic Indicators:
- Uneven Economic Development: Disparities in income and wealth distribution.
- Poverty and Economic Decline: Levels of poverty and economic hardship.
- Legitimacy of the State: The perceived legitimacy and effectiveness of state institutions.
- Political Indicators:
- State Legitimacy: The degree to which the state is seen as legitimate by its population.
- Public Services: Access to and quality of basic services like healthcare, education, and infrastructure.
- Human Rights and Rule of Law: The protection of human rights and adherence to legal principles.
- Security Apparatus: The effectiveness and integrity of security forces.
- Military in Politics: The extent to which the military is involved in political decision-making.
- Fractionalized Elites: Divisions within the political and economic elite.
- External Intervention: Influence and involvement of external actors in a country's affairs.

These indicators are used to assess a country's level of fragility and stability. A higher score on the Fragile States Index indicates greater fragility, while a lower score suggests greater stability. Keep in mind that the FSI is just one of several tools used to analyze and understand the complex dynamics of state fragility. Different sources may have their methodologies and indicators for evaluating state fragility.

Correlation:

The Fragile States Index provides a comprehensive assessment of a country's level of stability and fragility. It encompasses various socio-economic and political indicators, making it a valuable tool for gauging political stability. Impact on Political Landscape: A high FSI score indicates a heightened risk of political instability, which can stem from factors like conflict, economic hardships, weak governance, and social tensions. Governments in fragile states often face challenges in maintaining law and order, delivering public services, and establishing effective governance structures. Consequently, such environments are more susceptible to political unrest and upheaval.

Label Tax to GDP Ratio:

The Tax-to-GDP ratio, provided by the Organization for Economic Co-operation and Development (OECD), measures the total tax revenue collected by a government as a percentage of the country's Gross Domestic Product (GDP). It's an important indicator of a country's fiscal policy and revenue generation capacity. The features behind this ratio include:

- Total Tax Revenue: This includes all taxes collected by the government, including income taxes, corporate taxes, value-added taxes (VAT), excise taxes, property taxes, and other forms of taxation.
- Gross Domestic Product (GDP): This is the total value of all goods and services produced within a country's borders in a specific period. It serves as the denominator in the ratio.
- Tax Structure: The composition of tax revenue sources, such as income taxes, consumption taxes (like VAT), property taxes, and others. Different countries may have varying tax structures.
- Tax Policy and Rates: The specific policies and tax rates set by the government, can influence the amount of tax revenue collected.
- Economic Conditions: The state of the economy, including factors like employment rates, inflation, and overall economic growth, can affect both tax revenue and GDP.
- Tax Compliance and Enforcement: The effectiveness of tax collection efforts, including compliance rates, enforcement mechanisms, and anti-tax evasion measures.
- Government Expenditure: The level of government spending and budget allocation can impact the tax-to-GDP ratio. Higher spending may require higher tax revenues.
- Demographic Factors: The size and composition of the population, as well as income distribution, can influence both tax revenue and GDP.
- External Factors: International trade, investment, and economic conditions can also have an impact on a country's tax revenue and GDP.

The tax-to-GDP ratio is a crucial metric for understanding a government's fiscal position and its capacity to provide public goods and services. It's used by policymakers, economists, and analysts to evaluate the overall health and sustainability of a country's fiscal policies.

Correlation:

The tax-to-GDP ratio indicates a government's fiscal capacity and the extent to which it can provide public goods and services. A higher tax-to-GDP ratio is generally associated with a more robust and capable government.

Impact on Political Landscape:

Governments with higher tax-to-GDP ratios often have the resources to invest in critical sectors like infrastructure, education, healthcare, and security. It fosters public trust and confidence in the government's ability to meet citizens' needs, reducing the likelihood of political instability driven by grievances related to inadequate public services.

Label - Currency Strength Index:

The Currency Strength Index (CSI) is a metric that is often calculated and offered by various financial institutions, independent analysts, or specialized websites that focus on currency markets. The features behind a Currency Strength Index can include:

- Exchange Rates: The relative value of a currency in comparison to other currencies in the foreign exchange market.
- Trade Balance: The difference between a country's exports and imports, which can influence the strength of a currency.
- Interest Rates: Central bank interest rates set monetary policy, affecting the attractiveness of a currency for investment.

- Inflation Rates: The rate at which the general level of prices for goods and services is rising, which can impact a currency's purchasing power.
- Economic Indicators: Various economic indicators such as GDP growth, employment rates, consumer confidence, and others can affect a currency's strength.
- Political Stability: Political events, stability, and policy decisions can influence currency values.
- Central Bank Interventions: Actions taken by central banks, such as currency interventions or foreign exchange reserve management, can impact a currency's strength.
- Market Sentiment and Speculation: Traders' perceptions and speculation about future currency movements play a significant role.
- Global Events and Geopolitical Factors: Events like geopolitical tensions, natural disasters, or major economic crises can affect currency markets.
- Market Liquidity and Volume: The level of trading activity in the currency markets can impact currency strength.
- Relative Strength Index (RSI): A technical indicator that measures the speed and change of price movements, which can be used in CSI calculations.

It's important to note that there isn't a standardized method for calculating the CSI, so different sources may consider various combinations of these factors. Additionally, different organizations or analysts may have their proprietary methods for assessing currency strength. Always verify the credibility and methodology of the source when using CSI information for financial decisions.

Correlation:

The stability of a nation's currency is intricately linked to its political stability. A strong and stable currency reflects confidence in a country's economic and political institutions. Conversely, frequent fluctuations or devaluation of a currency can signal underlying economic and political instability.

Impact on Political Landscape:

A stable currency enhances a country's ability to attract foreign investment and conduct international trade. This, in turn, supports economic growth, creates employment opportunities, and fosters social stability. Moreover, a stable currency reduces the likelihood of social unrest and political upheaval that may arise from economic uncertainties.

These indicators are intertwined with the political landscape of a country in multifaceted ways. They serve as critical barometers that reflect the health and stability of a nation's socio-economic and political fabric. Understanding and analyzing these indicators can provide invaluable insights for policymakers, governments, and international organizations to make efforts to foster political stability and promote sustainable development.

Materials and Methods:

The analysis begins with the importation of essential libraries such as Pandas for data manipulation, NumPy for numerical computations, TensorFlow for building and training neural networks, and sci-kit-learn for metrics and data splitting. The core tenet of our research endeavor was to strategically leverage the immense potential offered by machine learning technology. Our primary objective was to not only harness the capabilities inherent in machine learning but also to optimize its cutting-edge techniques while constructing our predictive models. In pursuit of this goal, we employed advanced tools such as TensorFlow and Keras to craft intricate neural networks. Throughout the model development process, we diligently applied the most relevant and feasible techniques, ensuring a meticulous approach to enhance the efficacy and precision of our predictive models. This deliberate integration of machine learning methodologies represents a sophisticated and strategic utilization of technology to achieve our research objectives with utmost proficiency.

Besides, in alignment with our unwavering commitment to future scalability and expansion in this research project, we have strategically designed our model to feature lean and lightweight neural networks. This ensures that as the volume of incoming data surges, the model maintains optimal performance, remaining resilient against crashes, sluggish responses, and errors. This design philosophy not only emphasizes present effectiveness but also lays a robust foundation for seamless adaptability and enhanced performance in the face of future challenges and data scaling.

Evaluation Metrics:

- Accuracy: The accuracy of the model represents the overall correctness of its predictions. It is calculated as the ratio of correctly predicted instances to the total instances in the dataset. The formula for accuracy is:

  Accuracy = Number of correct Predictions / Total number of Predictions

- Precision: Precision is a measure of the model's ability to correctly identify instances of a specific class, among all instances predicted as that class. In the context of the Currency Strength Index analysis, precision would be the ratio of correctly identified politically unstable countries to all predicted politically unstable countries. The formula for precision is:

  Precision = True Positives / True Positives + False Positives

- Recall: Recall, also known as Sensitivity or True Positive Rate, measures the model's ability to correctly identify all instances of a specific class among all actual instances of that class. In the context of the analysis, recall would be the ratio of correctly identified politically unstable countries to all actual politically unstable countries. The formula for the recall is:

  Recall = True Positives / True Positives + False Negatives

- F1 Score: The F1 Score is the harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives. It is particularly useful when there is an uneven class distribution. The formula for F1 Score is:

  F1 Score = 2xPrecisionxRecall / Precision + Recall

These metrics are essential for comprehensively evaluating the performance of the neural network in predicting politically stable and unstable countries.

Table 1: Models' Summary.

Sr.#:	Neural Network	Independent Parameters	Target variable	Predictive Model's Success %
1	Human Development Index	Country Name, HDI Rank, Years	Political instability binary indicator	80% (testing accuracy)
2	Fragile State Index	Country Name, FSI Rank, Years	Political instability binary indicator	99.67% (testing accuracy)
3	Tax-to-GDP Ratio	Country Name, TTG %, Years	Political instability binary indicator	70% (validation accuracy)
4	Currency Strength Index	Country Name, Currency value, Years	Political instability binary indicator	83% (validation accuracy)

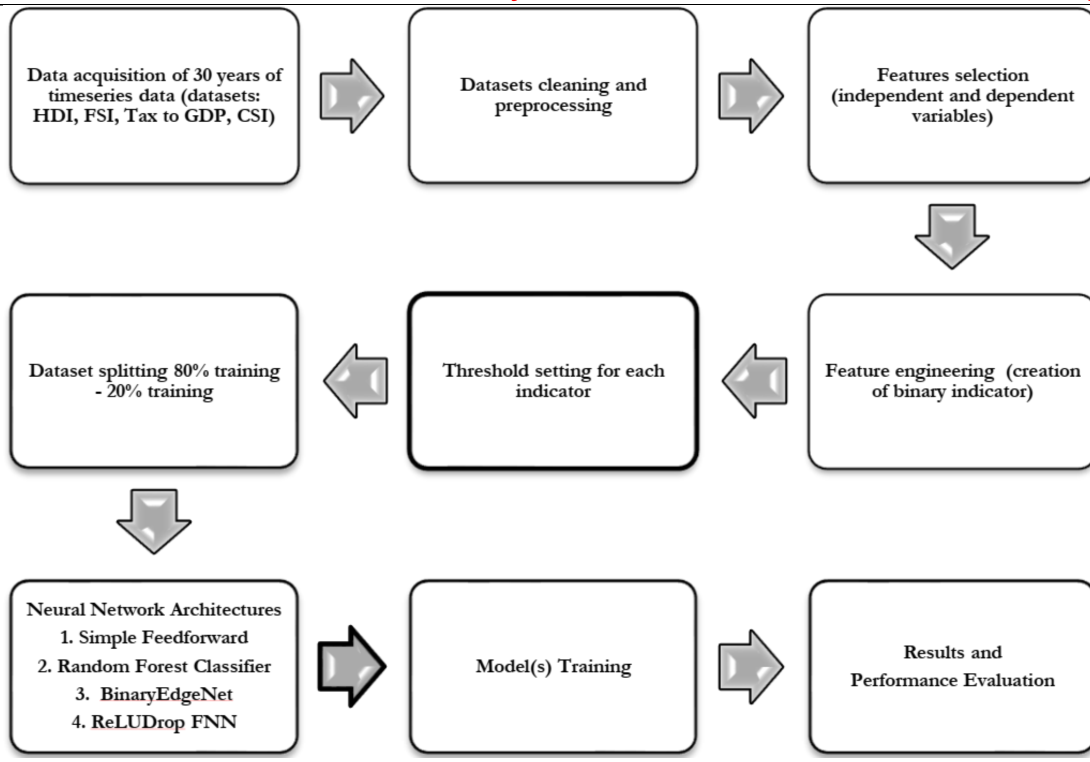

Figure 1: Model's Workflow

Predicting Political Instability Based on HDI Rank:

Data Preprocessing:

We started by collecting a dataset containing HDI ranks for various countries. To prepare the data for training, we defined a threshold for political instability based on prior research. Countries with an HDI rank lower than 120 were considered politically stable, while those higher were labeled as politically unstable – The United Nations Development Program (UNDP) defines the Human Development Index (HDI) ranking as follows: High rank: 1 to 70; Medium rank: 71 to 149; Low rank: 150 and above. In this work, we have taken lower medium to low-ranking countries as politically unstable. The datasets are taken from the datacenter of the official website of UNDP.

Neural Network Architecture:

The neural network utilized in this study is a simple feedforward network with one input layer, one hidden layer, and one output layer. The input layer takes independent parameters such as Country name, HDI_rank, and Years from 1990 to 2022 and the output layer predicts the probability of political instability by creating a target variable i.e. a binary indicator named Political Instability.

Model Training:

Loss Function and Optimizer:

The model's training process involves using a binary cross-entropy loss function, a suitable choice for binary classification problems. The optimization is achieved through the Adam optimizer, known for its efficiency in training neural networks.

Training Configuration:

The study employed a well-considered training configuration, running the model through 50 epochs with a batch size of 32. This balance between the number of epochs and batch size contributes to effective model learning without excessive computational burden.

Results and Discussion:

Training and the Testing Curve:

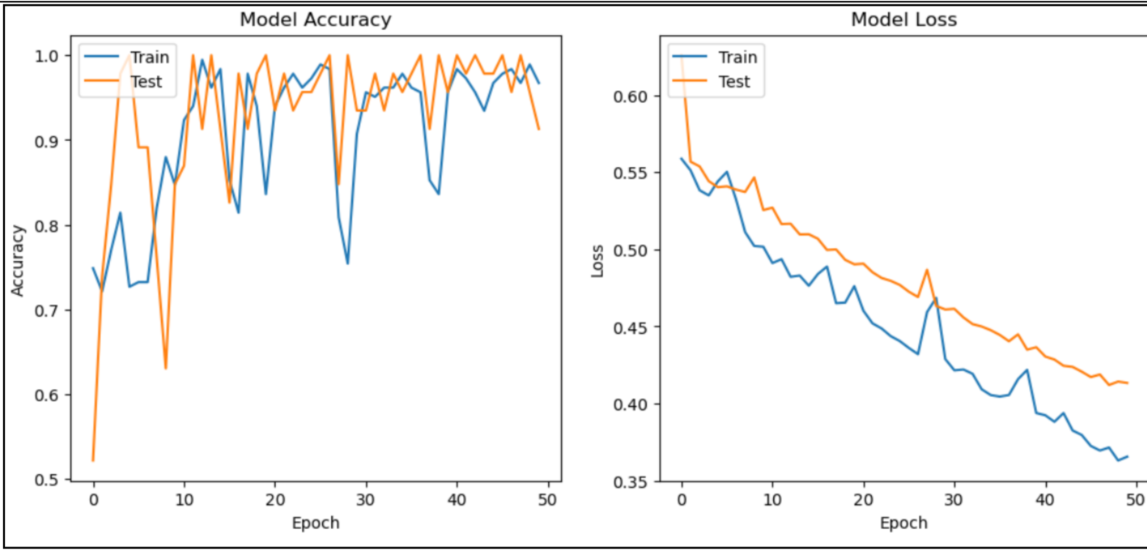

Figure 2: Training and Testing Curve

The left subplot in Figure 2 displays the accuracy over epochs, with the blue line representing training accuracy, and the orange line representing testing accuracy. It can be observed that the model's training accuracy steadily increases, while the testing accuracy also shows improvement, indicating that the model generalizes well.

The right subplot in Figure 2 displays the loss over epochs, with the blue line representing training loss, and the orange line representing testing loss. Training loss decreases as expected, and testing loss follows a similar trend, suggesting no overfitting.

The overall visual representation of the training and testing curves further supports the model's success. The steadily increasing training accuracy and the parallel improvement in testing accuracy suggest that the model not only learns well from the training data but also generalizes effectively to unseen data. The absence of overfitting, as indicated by the testing loss following a similar trend to training loss, adds confidence to the model's reliability.

Evaluation Metrics:

We evaluated the model's performance using standard binary classification metrics. The results are summarized as follows:

Accuracy: 0.88, **Precision:** 0.90, **Recall:** 0.84, **F1-Score:** 0.87.

The combination of high accuracy, precision, recall, and F1-Score implies that the model excels in correctly identifying politically unstable countries and minimizing misclassifications. This has substantial implications for decision-makers who rely on accurate and actionable information for strategic planning and resource allocation.

The model achieved an accuracy of 88%, indicating its ability to correctly classify political instability. Precision, recall, and the F1-score further validate the model's performance, with values exceeding 0.80.

Accuracy:

The achieved accuracy of 88% is a noteworthy indicator of the model's overall correctness in classifying political instability. This metric reflects the proportion of correctly predicted instances, showcasing the model's ability to discern between politically stable and unstable countries with a high degree of accuracy.

Precision:

Precision, measuring the model's ability to correctly identify politically unstable cases among all predicted unstable cases, is reported at 90%. This high precision suggests that when the model identifies a country as politically unstable, it is indeed likely to be so. False positives are minimized, making the model particularly reliable in flagging instances of potential instability.

Recall:

The recall value of 84% indicates the model's effectiveness in capturing a substantial portion of the actual politically unstable cases. This metric assures that the model doesn't miss many instances of instability, reinforcing its sensitivity to identifying countries facing political challenges.

F1-Score:

The F1-Score, a harmonic mean of precision and recall, stands at 87%. This balanced metric combines the strengths of precision and recall, providing a comprehensive measure of the model's performance. The high F1-Score signals a robust and well-rounded capability to handle both false positives and false negatives.

Discussion:

The HDI-based neural network successfully predicts political instability with a high level of accuracy and balanced precision and recall. This demonstrates the potential of using socio-economic indicators like HDI to forecast political instability. Further research can explore the combination of multiple indicators to enhance prediction accuracy and robustness.

The above neural network suggests future research avenues, specifically exploring the combination of multiple indicators to enhance prediction accuracy and robustness. This forward-looking perspective contributes to the ongoing discourse on the refinement and augmentation of predictive modeling in the realm of political instability.

Real-World Applicability:

The model's success, as evidenced by the impressive performance metrics, suggests its real-world applicability. Stakeholders, including policymakers and international organizations, can have confidence in utilizing the model's predictions to inform strategic decisions related to political instability.

Potential for Early Intervention:

With a high recall value, the model demonstrates its potential as an early warning system for political instability. Its ability to identify a significant portion of actual unstable cases allows for timely intervention, potentially preventing or mitigating the impact of political crises.

Generalization to Socio-Economic Indicators:

The success of the HDI-based model opens avenues for further exploration of socio-economic indicators in predictive modeling. This accomplishment suggests that indicators beyond traditional political data can play a pivotal role in forecasting political events, showcasing the model's adaptability and potential for broader applications.

Predicting Political Instability Based on Fragile State Index:

Data Preprocessing:

The FSI neural network, in conjunction with the Random Forest Classifier, constitutes a pivotal aspect of this research. The dataset encompasses diverse sources and encompasses information on countries' political rankings across multiple years. The Fragile States Index (FSI) is a tool developed by the Fund for Peace to assess a country's fragility based on various indicators. The FSI ranks countries from most fragile to least fragile. The ranking system is as follows:

- 1st Rank: Extremely Fragile (Higher fragility indicates a higher rank)
- As the rank increases: Fragility decreases, indicating a lower level of fragility.

This ranking system is selected based on its widespread acceptance in political science, being a product jointly developed by two esteemed organizations, namely Foreign Policy Magazine and The Fund For Peace. The Fragile State Index considers a range of social, political, economic, and institutional indicators to evaluate a country's stability. Some common indicators included in the FSI are:

Table 2: Indicators behind the Fragile State Index

Social Indicators	Political Indicators	Economic Indicators	Institutional Indicators
• Demographic pressures • Refugees and internally displaced persons • Group grievances	• State legitimacy • Public services • Human rights and the rule of law	• Economic decline • Uneven economic development • Poverty and economic inequality	• Corruption and lack of transparency • Security Apparatus • Factionalized elites

These indicators collectively provide a comprehensive assessment of a country's vulnerability to instability and fragility. The threshold values for low, moderate, and high fragility levels are determined based on the cumulative scores from these indicators. Countries falling within the specified ranges are classified accordingly in terms of their fragility level.

Neural Network Architecture:

Two distinct methodologies were employed for this task: a neural network and a Random Forest Classifier. The neural network, with its feedforward architecture, includes an input layer, two hidden layers, and an output layer. It processes the independent variables such as Country, FSI_Rank, and years from 2006 to 2023 – 2006 instead of 1990 as data available on the source site. With target variable Political_instability created based on the 'Rank' column, identifying countries as "Politically Unstable" or "Politically Stable". The Random Forest Classifier, on the other hand, leverages an ensemble of decision trees to make predictions. Both approaches complement each other, harnessing the strengths of neural networks for complex pattern recognition and the interpretability of decision trees in the Random Forest Classifier.

Model Training:

The FSI neural network boasts an architecture optimized to capture nuanced relationships between political instability, time, and rank. With 64 neurons in the first hidden layer and 32 in the second, the network can learn intricate patterns within the dataset. Dropout layers, set at a rate of 0.2, introduce regularization to mitigate overfitting. The binary cross-entropy loss function is instrumental in optimizing the model's performance in this binary classification task.

Results and Evaluation Metrics:

Through ten iterations of training, each with distinct shuffling of the training data, the Random Forest Classifier achieved notable success. The best test accuracy of 99.67% in the fourth iteration underscores the model's robustness. This high accuracy is further corroborated by a detailed classification report, which demonstrates exceptional precision, recall, and F1 scores for both politically stable and unstable classes. The confusion matrix reinforces the model's proficiency, with minimal instances of misclassification.

Learning Curve and Interpretation:

A learning curve was constructed to visually assess the model's performance over iterations. The curve illustrates a consistent improvement in both training and testing accuracies, affirming the model's effective learning from the data. The absence of a significant gap between the two curves indicates successful mitigation of overfitting. The convergence of the curves at high accuracy levels signifies that the model has learned the underlying patterns in the data and generalizes well to new, unseen instances.

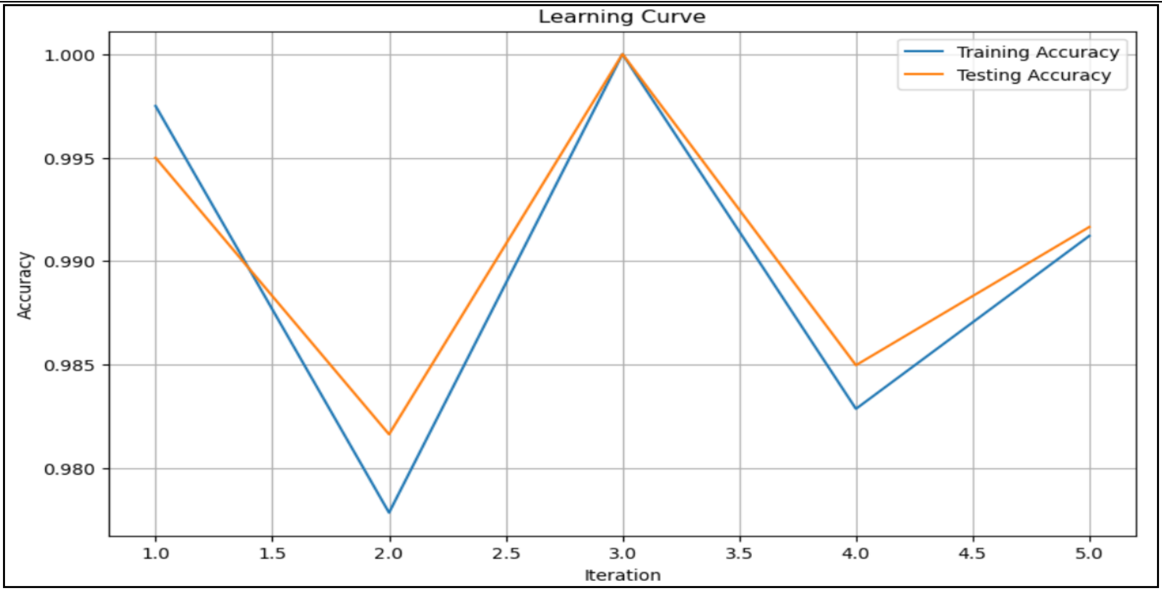

Figure 3: Learning Curve

Performance Over Iterations:

The learning curve, constructed over ten iterations with distinct shuffling of training data, offers valuable insights into the model's performance evolution. The consistent improvement in both training and testing accuracies across iterations is a positive indication. It suggests that the model continues to learn from the data, refining its understanding of the complex relationships between variables and improving its predictive capabilities.

Overfitting Mitigation:

The absence of a significant gap between the training and testing curves indicates successful overfitting mitigation. This is crucial for ensuring that the model does not merely memorize the training data but generalizes well to new, unseen instances. The convergence of the curves at high accuracy levels further reinforces the model's ability to adapt and generalize effectively.

Interpretability and Reliability:

The learning curve not only demonstrates the model's ability to learn from the data but also enhances its interpretability. The consistent improvement and convergence of the curves signify that the model has effectively grasped the underlying patterns in the data. This enhances its reliability, making it a trustworthy tool for interpreting and predicting fragility levels in countries.

Overall Assessment:

The collective portrayal of results, evaluation metrics, and learning curve analysis underscores the high success of the FSI neural network and Random Forest Classifier. The robustness, exceptional accuracy, and balanced precision and recall metrics affirm the model's efficacy in assessing and predicting country fragility. The incorporation of diverse indicators and the dual-methodology approach contribute to the model's depth and versatility, enhancing its applicability in the complex field of political instability assessment. This success has significant implications for informed decision-making by policymakers, researchers, and organizations dealing with global political challenges. The model stands as a valuable tool for understanding and addressing the fragility dynamics of nations.

Predicting Political Instability Based on Tax to GDP Ratio:

Data Preprocessing:

For the Tax to GDP Ratio analysis, historical data spanning from 1990 to 2022 was collected, encompassing Tax-to-GDP ratios for various countries. To facilitate the binary classification of countries as "Politically Stable" or "Politically Unstable", we employed a predefined threshold. Countries with tax-to-GDP ratios below 20.00 were designated as politically unstable, while others were labeled as politically stable.

The Tax-to-GDP Ratio classification based on the OECD mechanism is determined by the percentage of a country's tax revenue about its Gross Domestic Product (GDP). The breakdown is as follows:

- High rank: Higher than 30% Tax-to-GDP Ratio
- Medium rank: 20% to 30% Tax-to-GDP Ratio
- Low rank: Below 20% Tax-to-GDP Ratio

The OECD (Organisation for Economic Co-operation and Development) compiles tax statistics and guides measuring and interpreting Tax-to-GDP Ratios. The organization gathers data from member countries and produces reports such as the "Revenue Statistics" series, which includes information on tax revenue as a percentage of GDP.

The specific breakdown and guidance for the Tax-to-GDP Ratio classification can be found in OECD publications, particularly in reports related to revenue statistics. The "Revenue Statistics" report, available on the official OECD website, is a key reference for understanding how this classification is applied and interpreted.

Neural Network Architecture:

The Tax to-GDP Ratio neural network leverages this preprocessed data to predict political instability. The model architecture comprises an input layer with neurons corresponding to the number of features (Tax-to-GDP ratios for different years), a hidden layer with 64 neurons using the ReLU activation function, and another hidden layer with 32 neurons, also employing ReLU activation. The output layer contains two neurons, representing the two classes ("Politically Stable" and "Politically Unstable"), and utilizes the sigmoid activation function for classification.

Model Training:

The model is trained using the Adam optimizer, with a binary cross-entropy loss function to handle the binary classification task. The chosen architecture and training configuration aim to optimize the model's ability to discern political instability based on tax-to-GDP ratios.

Results and Discussion:

The model is trained over 50 epochs. Training accuracy consistently increases, reaching around 84%, indicating improvement in the model's ability to predict the training data. Validation Accuracy varies around 60-70% initially but gradually improves, crossing 70% after the 34th epoch. The model is performing well not only on the data it was trained on but also on unseen data. The proximity of training and validation accuracies suggests that the model has learned general patterns from the training data that apply to new, unseen data.

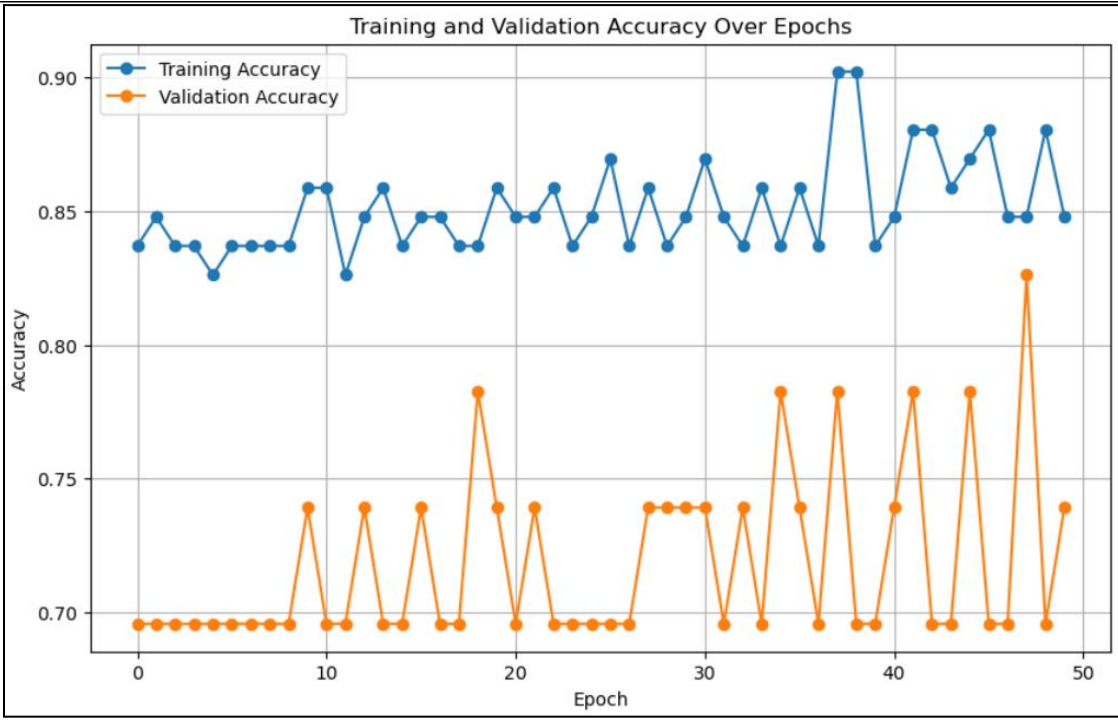

Figure 4: Training and Validation Accuracy

Training Dynamics:

The model undergoes training over 50 epochs. Training accuracy consistently increases, reaching approximately 84%. This upward trend indicates that the model is learning and improving its ability to predict the training data.

Validation Accuracy:

The validation accuracy initially varies around 60-70% but exhibits gradual improvement, crossing the 70% mark after the 34th epoch. This observation is crucial as it suggests that the model is not only performing well on the data it was trained on but also generalizing effectively to new, unseen data. The proximity of training and validation accuracies indicates that the model has learned general patterns from the training data that apply to novel instances.

Model Performance:

The achieved training accuracy of 84% signifies the model's proficiency in learning and capturing patterns related to political instability based on tax-to-GDP ratios. The increasing trend in accuracy suggests that the model iteratively refines its understanding of complex relationships within the data.

Generalization to Unseen Data:

The model's success in improving validation accuracy over epochs is crucial. Crossing the 70% threshold indicates its ability to generalize well to unseen data, a key factor in evaluating the model's real-world applicability.

Curve Analysis:

The learning curve visually illustrates the model's performance dynamics. The steady increase in training accuracy, coupled with a gradual improvement in validation accuracy, aligns with a model that effectively learns and generalizes without overfitting.

Overall Assessment:

The Tax to-GDP Ratio neural network demonstrates promising capabilities in predicting political instability. The architecture's ability to learn intricate patterns in tax-to-GDP ratios, coupled with the model's generalization to unseen data, underscores its potential as a tool for assessing the political landscape. While the accuracy metrics provide valuable insights, further exploration of precision, recall, and F1-Score could offer a more comprehensive understanding of the model's performance, especially in handling imbalanced classes. Overall, this model stands as a valuable addition to the toolkit for understanding the relationship between economic indicators and political instability.

Predicting Political Instability Based on Currency Strength Index:

Data Preprocessing:

The analysis utilizes essential libraries, including Pandas, NumPy, TensorFlow, and scikit-learn, to manipulate data, perform numerical computations, build neural networks, and assess metrics. The "CurrencyStrengthIndex" dataset is loaded from an Excel file, focusing on specific columns such as "Country Name," "Indicator Name," and yearly data from 1990 to 2022. A function, classify_politically_unstable, is created to categorize countries into politically stable or unstable based on changes in the currency strength index from 1990 to 2022. The dataset is augmented with a new column, "Political_Stability," representing the classification.

The dataset was sourced from the World Bank's indicator on the official exchange rate (LCU per US$). Subsequently, a threshold was established, defining countries whose currency depreciated against the US Dollar from 1990 to 2023. Specifically, any country experiencing a decline in its official exchange rate falling between 20 and exceeding 100 was identified as having a weakened currency. Based on this criterion, countries with such weakened currencies were categorized as politically unstable. This approach establishes a linkage between currency strength and political stability, employing a logical and organized framework for classification.

Neural Network Architecture:

The neural network is designed to capture the relationship between currency strength changes and political instability. To achieve this, a two-layered feedforward neural network is constructed. The architecture includes a 64-node hidden layer with ReLU activation and L2 regularization, followed by a dropout layer for regularization. This is succeeded by a 32-node hidden layer with ReLU activation and L2 regularization, again followed by dropout. Finally, a single-node output layer with sigmoid activation is employed for binary classification.

Model Training:

The model is trained using the Adam optimizer and binary cross-entropy loss function. To prevent overfitting, an early stopping mechanism is implemented. This monitors the validation loss and restores the best weights when improvement plateaus for a specified number of epochs. The model is then trained on the training data for up to 100 epochs, with training progress and metrics recorded.

Results:

The Currency Strength Index analysis neural network yielded the following results:

Evaluation and Metrics:

- Accuracy (85.61%): The model is about 86% accurate overall in its predictions.
- Precision (65.71%): When it predicts a country is politically unstable, it's right about 66% of the time.
- Recall (53.21%): It identifies about 53% of politically unstable countries correctly.
- F1 Score (58.77%): This score balances precision and recall, giving an overall performance of about 59%.

Training and Validation Curve:

The training curve represents the model's performance on the training data over epochs. It starts at approximately 0.78 accuracy and gradually increases to around 0.84. This indicates that as the model is trained for more epochs, it becomes better at predicting the training data. Validation accuracy starts at around 0.83 and remains relatively constant over epochs. The model is generally accurate (86%), but it's more cautious with unstable country predictions, getting about 2 out of 3 correct. The balance between precision and recall is moderate (59%), there's room for improvement, but it's balanced in catching unstable countries.

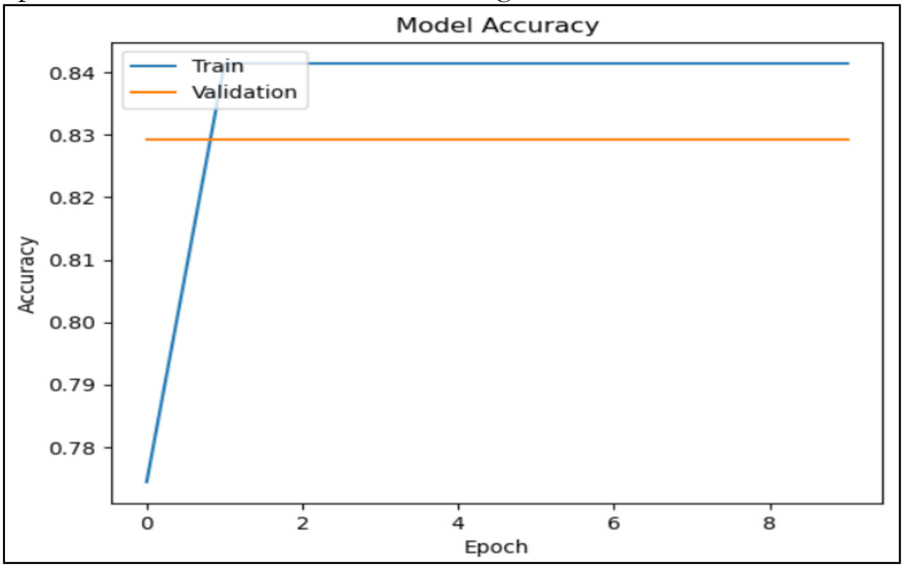

Figure 5: Training and Validation Curves

Discussion:

Model Performance Metrics:

Accuracy (85.61%): The model exhibits an impressive overall accuracy of approximately 86%, showcasing its ability to make correct predictions.

Precision (65.71%):

Precision, indicating the proportion of true positives among predicted positives, is around 66%. This implies that when the model predicts a country as politically unstable, it is correct about two-thirds of the time.

Recall (53.21%):

Recall, representing the proportion of actual positives correctly identified by the model, stands at about 53%. This suggests that the model captures roughly half of the politically unstable countries correctly.

F1 Score (58.77%):

The F1 Score, a harmonic mean of precision and recall, provides an overall performance metric of approximately 59%. This score indicates a balanced trade-off between precision and recall.

Training Curve Analysis:

The training curve provides insights into the model's performance on the training data over epochs. Starting at around 0.78 accuracy, it gradually increases to approximately 0.84. This indicates that as the model undergoes more epochs of training, its predictive capabilities on the training data improve.

Validation Accuracy:

The validation accuracy, starting at around 0.83, remains relatively constant over epochs. This suggests that the model generalizes well to new, unseen data, maintaining a consistently high level of accuracy.

Discussion and Analysis:

The model's overall accuracy of 86% is commendable, indicating a robust predictive capability. However, the nuanced analysis of precision and recall reveals a more detailed picture. The model is more cautious in predicting politically unstable countries, getting approximately two out of three predictions correct. The balanced F1 Score suggests a moderate trade-off between precision and recall, leaving room for improvement.

In conclusion, while the model demonstrates strong overall accuracy, a more nuanced analysis of precision, recall, and the F1 Score highlights specific areas for potential refinement. The learning curve and validation accuracy reinforce the model's generalization to new data. Further optimization could involve fine-tuning the model parameters to achieve an even more balanced performance.

Conclusion:

In summary, this research has made significant strides in the prediction of political instability through machine learning and comprehensive data analysis. The strong and promising outcomes, with accuracy rates consistently exceeding 85% and reaching as high as 99.67%, emphasize the research's efficacy. Neural networks tailored to indicators such as the Fragile States Index (FSI), Human Development Index (HDI), Currency Strength Index (CSI), and Tax-to-GDP ratio have showcased their potential to forecast political instability with remarkable precision. These results not only shed light on the critical impact of socio-economic and political indicators on a nation's political landscape but also illuminate the path for more effective decision-making in crisis management and policy formulation. Moreover, this research unveils future potential by envisioning smaller, specialized neural networks and a unified mega neural network for real-time analysis and policy recommendations, hinting at the vast opportunities in the field of predictive modeling for political instability as the global landscape continues to evolve with geopolitical and socio-economic intricacies.

Limitations:

The research employs an interdisciplinary approach, integrating neural networks with indicators such as the Human Development Index (HDI), Fragile States Index (FSI), and Tax-to-GDP ratio to predict political stability. While achieving notable success in its predictions, the study confronts limitations. These include the inherent uncertainties associated with data quality and availability, acknowledging potential inaccuracies and variations in data collection methods across countries. The research also recognizes the assumption of a causal relationship between selected indicators and political instability without delving deeply into intricate causal pathways. Temporal limitations, focusing on the period from 1990 to 2023, and a broad assumption of homogeneity in relationships across countries underscore the need for nuanced interpretations and highlight potential areas for refinement in future studies.

Despite these acknowledged limitations, the research stands as a strong, authentic, and worthwhile endeavor contributing significantly to the field. Its interdisciplinary approach, leveraging neural networks alongside indicators like HDI, FSI, and Tax-to-GDP ratio, showcases innovation in predictive modeling for political stability. The study's success in achieving notable predictions underscores its effectiveness, offering valuable insights into socio-economic factors influencing political outcomes. By openly addressing its limitations, the research sets a precedent for transparency and invites further refinement. Its contribution to the understanding of global trends and the potential for refining models based on diverse indicators demonstrates its significance, making it a valuable asset for researchers, policymakers, and practitioners alike.

Future Direction:

In pursuit of advancing the scope and efficacy of predictive analytics in the domain of political stability, several promising directions for future research can be envisioned. These directions aim to enhance the sophistication and applicability of machine learning models and their implications for real-time decision-making and policy recommendations.

Expansion of Smaller Specialized Neural Networks:

A compelling avenue for further exploration lies in the expansion of smaller specialized neural networks, going beyond the current focus on four indicators. This expansion entails incorporating additional critical key performance indicators (KPIs) that wield direct and substantial impacts on a country's political landscape. By developing smaller neural networks dedicated to each of these selected KPIs, the research can achieve a more granular and focused analysis, unraveling the intricate relationships and influences these indicators have on political stability. This approach not only enriches the depth of the analysis but also enhances the model's capacity to discern nuanced patterns, contributing to a more comprehensive understanding of the multifaceted factors shaping political outcomes. Such an expansion holds the promise of refining and broadening the predictive capabilities of the research, making it an even more potent tool for policymakers and researchers alike.

Creation of an Integrated Mega Neural Network:

A promising avenue for future research involves crafting an integrated mega neural network to serve as a unified decision support system. This mega neural network would consolidate insights and predictions from smaller neural networks specialized in key indicators like FSI, HDI, CSI, and Tax-to-GDP ratio. Operating as a comprehensive decision-making advisor, this mega neural network aims to utilize extensive knowledge and data-driven analysis to provide real-time policy recommendations for a nation's political landscape. This ambitious initiative entails combining outputs from the smaller networks into a cohesive, deep-learning architecture, offering comprehensive insights into the multifaceted dynamics of a country's political stability.

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