Poster: Predicting Internet Shutdowns - A Machine Learning Approach

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ABSTRACT

Internet shutdowns, often enforced by governments to control communication and access to information, have significant socio-political and economic implications. This study presents a machine learning approach to predict the likelihood of internet shutdowns, developing an Internet Shutdown Risk Score using public datasets from 125 countries. A Random Forest classifier, achieving an AUC of 0.97, was used to calculate risk scores. Key features were identified using the Shapley algorithm, highlighting factors like political unrest, economic conditions, and digital infrastructure. Case studies in Pakistan, India, and Sudan demonstrate rising shutdown risks due to protests from 2019 to 2022. Globally, the Internet Shutdown Risk Index has been consistently high since 2019, indicating increased threats of internet shutdowns in politically unstable regions.

CCS CONCEPTS

• **Computing methodologies → Feature selection**.

KEYWORDS

Internet shutdowns, Random Forest, shutdown risk prediction

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1 INTRODUCTION

Internet shutdowns are government-ordered blocks on Internet access, often to disrupt communication and restrict information. Internet shutdowns cause significant economic losses in terms of GDP, foreign direct investment (FDI) or employment opportunities [1]. They have become an urgent issue due to their increasing frequency, with 283 shutdowns in 39 countries during protests in 2023 often linked to hiding human rights abuses and violence. India only had the 167 shutdown events in 2023. From 2019 to 2023, shutdowns were mainly due to mass demonstrations, conflicts, elections, and school exams. Hence, we develop a model to predict Internet shutdowns based on key predictors such as the current unrest, inflation, unrest in neighboring states, and digital media usage. The study uses data from 125 countries and over 340 indicators.

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2 DATA

We build our model by using the following *publicly available* datasets: (1) **Shutdowns data:** Detailed event-level data from the Internet Society Pulse Platform (ISOC Pulse, henceforth), [2], (2)**Protests and civil unrest:** The Armed Conflict Location & Event Data Project (ACLED) provides detailed event-level data, [3], (3)**Elections:** From the Constituency-Level Elections Archive (CLEA) maintained by Yale University, [4], (4) **Economic indicators data**: include (GDP per capita in USD purchasing-power-parity terms, constant prices of 2011), employment (International Labor Organization or ILO estimates, separately for male and female), Inflation (percentage), Foreign Direct Investment (FDI, as a percentage of GDP as well as net inflows) from the World Bank, and finally (5) **Internet Resilience:** We use the Internet Society's Internet Resilience Index[5].

3 MODELS

3.1 Machine Learning Models Considered

We tested 27 different machine learning models and compared their accuracy, balanced accuracy, ROC AUC, F1 score, and time taken, the models were sorted. The models tested include Random Forest Classifier, XGB Classifier, ExtraTreesClassifier, LabelPropagation, LabelSpreading, LGBMClassifier, BaggingClassifier, DecisionTreeClassifier, and others. Considering the individual performance of each model, random forests performed better with an accuracy of 0.92 and a mean AUC of 0.97.

3.2 Model Evaluation and Performance

We used K-fold cross-validation to ensure a robust AUC and prevent over-fitting or under-fitting. With over 80,000 data points from shutdown cases across multiple countries, K-fold cross-validation, combined with hyper-parameter tuning, helped optimize model accuracy and AUC. Given the time-dependent nature of the dataset, this approach ensured consistency in performance. [6].

3.3 Feature Importance

To understand the importance of the different features in driving the model predictions, we use Shapely values [7]. It is useful to begin with the linear case to understand this approach to feature importance in non-linear models. The contribution of a feature or a single observation of that feature to a prediction in a linear model is given by the regression coefficients multiplied by the observation value(s). This approach to measuring feature importance in the machine learning literature is due to Stumble *et al.* [8].

4 RESULTS

4.1 Selected Features and model performance

The figure below shows a set of features driving the Internet Shutdown across the globe

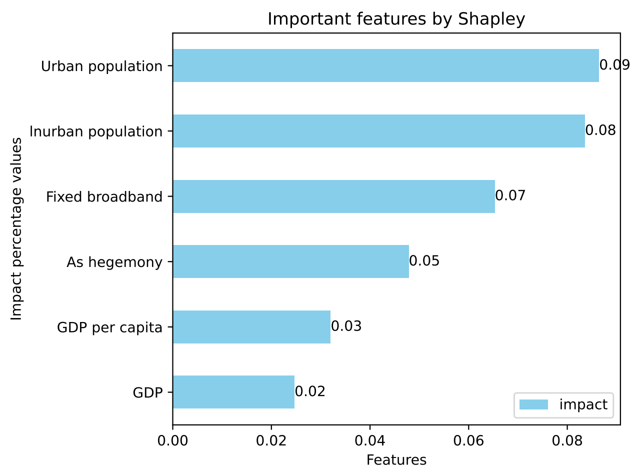

Figure 1: Significant features triggering Internet shutdowns

Figure 1 indicates that a mix of economic, political, and infrastructure factors determines the likelihood of an internet shutdown. Countries with higher GDP, better Internet infrastructure (fixed broadband and mobile subscribers), and more developed urban areas are less likely to experience Internet shutdowns, while political factors like as_hegemony[9] play a role in increasing the probability of such events. On the other hand, the model achieved the following accuracies for each year: 0.85 in 2022, 0.78 in 2021, 0.82 in 2020, and 0.72 in 2019. Considering the type of event, the accuracies are as follows: Riots, 0.83; Protests, 0.80; Violence, 0.69; Battles, 0.68; and Strategic violent targeting civilians, 0.64. The model performed poorly in 2019, likely due to the rumors and disruptions caused by COVID-19, which triggered numerous shutdowns. Riots were particularly associated with high accuracy in predicting Internet shutdowns.

4.2 Internet shutdown risk index

The model-generated probabilities, are referred to as the risk scores. The global risk scores show that 2020 had the highest likelihood of an Internet shutdown, with a risk index of 0.91, followed by 2021 with 0.84, while 2020 had 0.73, and 2019 with 0.76. These risk scores indicate a consistently high global risk score of an Internet shutdown, with probabilities exceeding 70% across all the four years analyzed.

4.3 Country Cases

The country-specific cases of Internet shutdown, such as protests, violence, riots, and battles, were analyzed for India, Pakistan, and Sudan from 2019 to 2022. The model provided historical values and predicted risk indices for these countries. The risk scores were 0.87 in 2022, 1 in 2021 and 2020, and 0.96 in 2019. This aligns with the rise in protests in India, peaking at 14,000 in 2020 before dropping to 4,000 in 2022. In 2020, India saw over 106 internet shutdowns, driven by events like the Citizenship Amendment Act protests, Article 370 repeal, and Farm Bills. Pakistan had similarly high-risk scores in 2021 and 2020, with 0.96 in 2019, linked to violence and bombings. [10–14]. Sudan exhibited a high risk in 2021, with risks of 0.87 in 2022 and 0.96 in 2029. Violence and battles dropped from around 200 cases in 2019 to below 50 in 2020 and 2021 [15]. In 2021, Sudan experienced over 400 protest cases, leading to increased hand-cast scores from 0.965 in 2019 to 1 in 2021. AccessNow reported multiple incidents in 2021, including protests that resulted in over 17 deaths and 250 injuries [16].

5 CONCLUSION

The machine learning model developed in this study effectively predicts the risk of internet shutdowns, with a high degree of accuracy. The results highlight the critical role of political instability, economic factors, and digital infrastructure in driving shutdown risks. The consistent global rise in shutdown risk since 2019 underscores the growing use of internet disruptions as a tool during periods of unrest. This predictive model provides valuable insights that could aid in preparing for or mitigating the impact of such events in vulnerable regions.

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