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A Literature Review on AI Powered Disaster Prediction using LSTM and PROPHET

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ABSTRACT :

The increasing frequency and severity of natural disasters such as floods, wildfires, earthquakes, and hurricanes largely driven by climate change have highlighted the urgent need for reliable and timely disaster prediction systems. Artificial Intelligence (AI), especially through time-series modeling, has emerged as a critical tool in enhancing disaster preparedness and response. This paper explores recent developments in the integration of AI-based models for catastrophe forecasting, specifically focusing on the combined use of Long Short-Term Memory (LSTM) networks and the Prophet algorithm. LSTM, a variant of Recurrent Neural Networks (RNN), is highly effective in capturing long-term dependencies and complex temporal patterns, making it suitable for modeling the irregular and dynamic nature of disaster-related data. On the other hand, Prophet, developed by Meta (formerly Facebook), is renowned for its ease of use, interpretability, and ability to handle missing data and outliers in time series forecasting. While LSTM excels in learning from complex sequences, Prophet is particularly effective in capturing seasonality and trend components. Studies have shown that hybrid models integrating LSTM and Prophet outperform single-model approaches, particularly in predicting events like rainfall, floods, and energy-related risks. This paper reviews such hybrid methodologies, evaluates their performance, and identifies current research gaps. It emphasizes the importance of multi-source data integration from sensors, satellites, and social media for enhancing prediction reliability, especially in remote or underdeveloped areas where data is often sparse or noisy. Furthermore, the paper addresses several critical challenges such as model integration complexity, computational demands for real-time predictions, risks of overfitting on small datasets, infrastructure constraints in deploying models in the field, and the lack of mechanisms to quantify prediction uncertainty.

Keywords: Disaster Prediction, Time-Series Forecasting, Long Short-Term Memory (LSTM), Prophet Algorithm, Artificial Intelligence (AI), Catastrophe Forecasting, Deep Learning, Recurrent Neural Networks (RNN), Multi-Source Data Integration.

1.INTRODUCTION

In later a long time, the recurrence and concentration of normal disasters such as surges, storms, dry seasons, and wildfires have expanded altogether due to the quickening impacts of climate alteration and urbanization. These occasions cause far-reaching disturbances to human life, financial foundation, and the environment. Compelling catastrophe administration has in this way gotten to be a worldwide need, especially in powerless locales. One of the foremost basic components of catastrophe administration is precise and opportune estimating, which can essentially diminish the scale of devastation by empowering early caution frameworks, hazard relief, and proficient asset allocation.

Traditional factual estimating models, such as ARIMA (Auto-Regressive Integrated Moving) and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) (Regular ARIMA), have been broadly utilized in disaster-related time-series forecasts. Whereas these models perform sensibly well beneath steady and straight conditions, they battle to capture complex nonlinear designs, sudden changes, and long-term conditions that are frequently shown in disaster-related information. Besides, they as a rule require huge sums of pre-processed and clean information, which is not continuously accessible in real-world catastrophe scenarios.
To overcome these impediments, the inquiry about community has progressively turned to machine learning (ML) and Deep learning (DL) strategies. Among these, Long Short-Term Memory (LSTM) networks an extraordinary sort of Recurrent neural arrangement (RNN) have appeared as noteworthy guarantee in modelling successive information with long-range transient conditions. LSTM can hold pertinent past data for longer periods, making it profoundly appropriate for calamity forecast assignments that depend on worldly designs, such as precipitation levels, water release rates, or temperature fluctuations.
On the other hand, Prophet could be a time-series determining show created by Facebook (presently Meta), planned to handle lost information, exceptions, and solid regular impacts. It breaks down a time arrangement into drift, regularity, and occasion components, making it especially viable for datasets with

solid occasional designs and abnormalities. Prophet is additionally user-friendly, requiring negligible parameter tuning, which makes it a well-known choice for professionals in both the scholarly world and industry.

Recent considerations have investigated cross-breed models that combine LSTM and Prophet, pointing to the use of the qualities of both. In these crossover systems, Prophet is ordinarily utilized to demonstrate drift and regularity, whereas LSTM is connected to the leftover or unexplained component of the time arrangement. This combination permits the show to handle both unsurprising and eccentric viewpoints of disaster-related information. Inquire conducted between 2021 and 2025 has illustrated the predominant execution of such half breeds in different applications, counting surge expectation, precipitation estimation, vitality request determining amid extraordinary climate, and tornado tracking.

This writing survey paper points to investigating, analyzing, and synthesizing later headways in cross-breed LSTM Prophet models for catastrophe estimating. The Centre is on surveying show designs, evaluating performance measurements, and recognizing key patterns within the field. Moreover, the paper talks about current challenges and holes within the investigation, such as constrained interpretability, information accessibility, and the requirement for real-time applications. The overarching objective is to supply a comprehensive understanding of how these AI-powered determining frameworks can contribute to more compelling and proactive calamity administration procedures.

2.RELATED WORK

To address the eccentrics and nonlinear nature of catastrophe information, later thinks about coordinates counterfeit insights approaches, particularly profound learning procedures. Early endeavours joined conventional LSTM systems to show long-term conditions in meteorological and hydrological information. Be that as it may, these models alone were frequently deficient for capturing regularity and drift irregularities.

In reaction, analysts started to create crossover designs, outstandingly combining LSTM with the Prophet show. These half-breed frameworks utilized Prophet for breaking down time-series components like drift and regularity, whereas LSTM has overseen leftover variances. One such execution illustrated moved forward exactness in precipitation expectation by confining unsurprising regular behaviour through Prophet, empowering LSTM to way better handle startling spikes and variations.

Advanced integrative have included CNN-LSTM models custom fitted for spatial-temporal surge expectation, where convolutional layers extricated spatial highlights sometime recently nourishing arrangements into LSTM units. These frameworks appeared solid execution in twofold and multiclass estimating errands, especially when connected to high-resolution lackey datasets. Whereas LSTM exceeds expectations in worldly relationships, CNN upgrades its capability in dealing with multidimensional information inputs.

Optimization strategies such as network look and Bayesian tuning have to been utilized to fine-tune hyperparameters in half-breed models. Thinks about having consolidated highlight determination instruments and dimensionality decrease strategies like PCA to progress computational effectiveness and diminish overfitting. These optimizations have been especially important when applying models to vitality utilization estimating amid calamity scenarios.

Although measurable models such as ARIMA and Arbitrary Timberland proceed to be utilized, their exactness decreases in profoundly nonlinear and regular calamity settings. Comparatively, Prophet LSTM cross breeds have reliably illustrated diminished RMSE and MAPE values over spaces counting dry spell expectation, violent wind following, and flood-level estimating. Later models joining consideration instruments and geospatial highlights into LSTM have encouraged progressed fiasco occasion location precision.

Despite these progressions, challenges hold on. Numerous models depend on precisely labelled and total datasets, which are not continuously accessible amid real-time fiasco events. Also, whereas half-breed models are more interpretable than black-box models, their arrangement in edge or low-resource situations remains constrained due to computational demands.

Overall, the writing from 2021 to 2025 uncovers a reliable slant: crossover LSTM Prophet systems beat single-model approaches in prescient precision, versatility, and regularity dealing with. Proceeded to inquire about cantering on upgrading these crossbreeds with spatial mindfulness, interpretability, and real-time capabilities.

3.OBJECTIVES

The essential objective of this consideration is to create a vigorous and brilliantly catastrophe expectation demonstrated by joining progressed AI-based determining methods, particularly Long Short-Term Memory (LSTM) systems and the Prophet show. This investigates points to upgrade the precision, interpretability, and unwavering quality of estimating common catastrophes such as surges, seismic tremors, and extraordinary climate occasions. The goals are sketched out below:

1. To Get it and Analyse Fiasco Designs Utilizing Chronicled Data

Collect and preprocess verifiable time-series information related to characteristic fiascos, counting precipitation, temperature, seismic movement, and water levels. Study the worldly and regular behaviour of the information to recognize key designs and factors affecting calamity occurrences.

2. To Actualize the LSTM Neural, Organize for Consecutive Forecasting

Apply LSTM systems to show the successive and long-term conditions in disaster-related data. Train the LSTM to foresee disaster-related results (e.g., precipitation concentrated, surge levels, seismic size) based on multivariate inputs.

3. To Utilize the Prophet, Show for Drift and Regularity Decomposition

Use Prophet to distinguish and demonstrate long-term patterns, occasional designs, and regularity within the data. Forecast future occasions based on verifiable regular vacillations and changepoints recognized by the Prophet model.

4. To Create a Crossover LSTM-Prophet Show for Improved Determining Accuracy

Integrate Prophet and LSTM into a crossover system where Prophet breaks down the time arrangement and LSTM is connected to remaining or combined data. Evaluate the execution of the half-breed demonstrated in capturing non-linear and unexpected calamity peculiarities that single models may miss.

5. To Compare the Execution of Person and Crossover Models

Assess and compare the expectation precision of Prophet, LSTM, and the cross breed demonstrate utilizing standard assessment measurements such as RMSE, MAE, and RÂ² score. Conduct case ponders on surge estimating, precipitation forecast, and seismic movement expectation to approve and demonstrate effectiveness.

6. To Address Commonsense Execution Challenges

Investigate challenges such as information restrictions, overfitting in profound learning models, and computational asset constraints. Explore strategies for demonstrating optimization, information augmentation, and real-time adaptability.

7. To Supply a Versatile System for Real-Time Catastrophe Early Caution Systems

Propose a down-to-earth execution methodology for coordinating the cross-breed demonstration into fiasco reaction systems. Explore the utilisation of IoT, cloud stages, and real-time dashboards for robotized alarm era and change communication.

4.PROPOSED METHODOLOGY

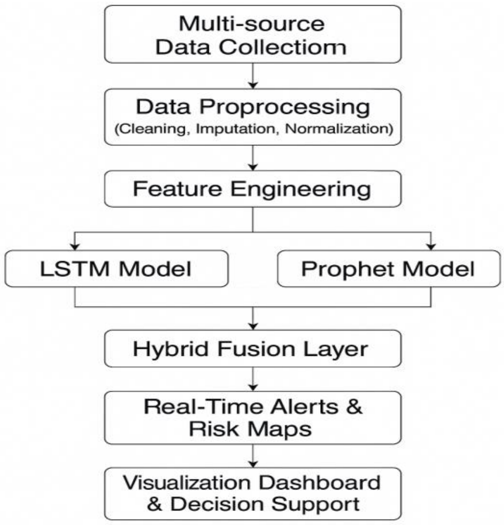

Fig 1: Architecture

The proposed technique points to creating a crossover determining show that combines the qualities of the Prophet show and Long Short-Term Memory (LSTM) neural systems for precise fiasco expectation. The technique starts with the collection and preprocessing of time-series information significant to characteristic catastrophes, such as precipitation concentration, temperature, stickiness, waterway water levels, or seismic movement, depending on the sort of fiasco beneath consider. Information is sourced from government meteorological offices, disciple datasets, and freely accessible geophysical databases. The preprocessing arrangement includes taking care of lost values, exception discovery, normalization, and change of the crude information into a organize appropriate for time-series modelling.

Once cleaned and organized, the dataset is to begin with passed through the Prophet demonstration, which breaks down the time arrangement into three components: slant, regularity, and residuals. Prophet is chosen for its capacity to handle non-linear patterns, annual and week-by-week regularity, and its strength to lost information and exceptions. The show estimates disaster-related factors based on these components and distinguishes changepoints where designs move significantly crucial for occasions like storm onset or structural changes.

The leftover component, which incorporates non-linear changes not captured by Prophet, is at that point utilized to prepare an LSTM neural arrangement. LSTM is well-suited for learning from successive information and capturing worldly conditions which will not take after normal patterns or regular designs. This permits the demonstration to foresee sudden catastrophe occasions like streak surges or seismic tremor tremors based on the complex behaviour of the residuals. The LSTM is prepared utilizing chronicled leftover information and tuned to utilize hyperparameter optimization methods such as grid look or irregular explore for made strides accuracy.

Finally, the outputs of both models Prophet and LSTM are combined in a weighted outfit to create the ultimate expectation. The model’s execution is assessed utilizing measurements such as Root Cruel Square Mistake (RMSE), Cruel Supreme Mistake (MAE), and R-squared (RÂ²) to guarantee estimating unwavering quality. The strategy moreover incorporates validation using test datasets or calamity case considers to confirm the model’s real-world pertinence. This half-breed approach points to supplying a versatile, precise, and interpretable determining apparatus appropriate for integration into early caution frameworks and catastrophe administration stages.

1. Data Collection and Preprocessing

The primary step in building an AI-powered fiasco forecast demonstrates includes collecting important and high-quality authentic information. The nature of the information depends on the sort of calamity to be anticipated. For occasion, surge expectation requires parameters such as precipitation, waterway water level, temperature, soil dampness, and mugginess, whereas seismic tremor estimating may utilize seismic waveform information, ground movement concentrated, and structural push levels. Information can be sourced from national meteorological organizations (e.g., IMD), inaccessible detecting satellites (e.g., NASA MODIS, NOAA), online open datasets (e.g., Kaggle, USGS), and IoT-based climate sensors.

Once the information is assembled, information preprocessing is fundamental to guarantee exactness and consistency this includes:

- Missing esteem is taken care of through insertion or imputation.
- Outlier location and expulsion utilizing measurable strategies such as z-score or IQR.
- Normalization or scaling of highlights utilizing Min-Max or Standard Scaler strategies to create information reasonable for LSTM inputs.
- Time list adjustment for arrangement, particularly in multi-source datasets.
- Data smoothing to dispose of irregular commotion, may prevent the model's learning process.

After cleaning, the time-series information is designed into consecutive windows/sliding windows as required by sequence-based models like LSTM. Highlight building is additionally performed where slack factors, rolling midpoints, and other time-based indicators are included to enhance the dataset.

2. Prophet Model for Decomposition and Forecasting

The Prophet demonstrates, created by Meta (Facebook), is utilized in this technique as a preparatory determining layer and for information decay. Prophet models the time arrangement as a combination of drift, regularity, and occasion impacts, which is particularly advantageous when managing with information that shows clear recurrent designs like rainstorms or annual climate anomalies.

This demonstration is vigorous to lost information, exceptions, and changepoints. It is utilized here to:

- Generate a base forecast.
- Extract residuals after subtracting drift and seasonality.
- Provide understanding of intermittent behaviours for calamity planning.

The residuals, which speak to eccentric and non-linear varieties (e.g., sudden surges, seismic tremors), are passed to the LSTM demonstrate, as Prophet alone cannot demonstrate these complex designs.

3. LSTM Model for Residual Learning and Temporal Prediction

The Long Short-Term Memory (LSTM) neural organize is at that point connected to demonstrate the complex remaining component cleared out over by Prophet. LSTM, a sort of Recurrent Neural Network (RNN), is particularly planned to memorize consecutive information and long-term conditions through its memory cell engineering. It overcomes the vanishing slope issue common in conventional RNNs.

The design involves:

- Input Layer: Gets a multivariate time window of past residuals and any other related features.
- Hidden LSTM Layers: Contain memory cells with disregard, input, and yield doors that control the stream of data over time.
- Dense Layer: The Last layer yields an expectation for future fiasco values (e.g., next-day precipitation or seismic magnitude).

The LSTM show is prepared to utilize Back Propagation Through Time (BPTT), and its hyperparameters (e.g., learning rate, number of LSTM units, clump measure, and ages) are tuned utilizing procedures like lattice look or Bayesian optimization.

To maintain a strategic distance from overfitting, dropout layers are included and preparation is observed with early ceasing based on approval misfortune. The show execution is assessed on test information using:

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Coefficient of Assurance (RÂ²)

This approach enables the show to memorize sporadic, extraordinary, or sudden designs not clarified by the seasonal-trend portion of the time arrangement.

5.Hybrid Forecast Generation and Evaluation

The ultimate estimate is created by combining the yields from both the Prophet and LSTM models. Two approaches are considered:

- Additive Combination:

Final estimate = Prophet estimate + LSTM figure of residuals
This strategy employments the Prophet's organized expectations and expands them with LSTMs redress on the unusual parts.

- Weighted Outfit:

The Weighted normal of both shows yields where weights are decided based on execution measurements from approval datasets.

The cross-breed show is at that point assessed and compared against standalone LSTM and Prophet models. The comparison incorporates visualization of forecasts, genuine catastrophe occasions, and blunder measurements. Case considers are conducted, for occurrence, estimating waterway flood amid storm or precipitation spikes amid violent wind occasions.

6.CHALLENGES AND IMPROVEMENTS

1. Data Quality and Availability
Disaster-related data is often incomplete, noisy, or missing, especially in remote or undeveloped areas. To overcome this, data from multiple sources like sensors, social media, and disciples are integrated, and Prophet is used alongside LSTM to improve the reliability of learning.
2. Model Integration Complexity
Integrating LSTM and Prophet models is challenging due to differences in their structure and time resolution. A crossover combination layer helps align their outputs through techniques like weighted averaging and tuning based on error.
3. Real-Time Handling Limitations
LSTM models are resource-heavy, making it difficult to respond quickly during emergencies. To improve real-time performance, dimensionality reduction, flexible architecture, and interactive dashboards are used to enhance speed and clarity.
4. Overfitting and Restricted Generalization
LSTMs may overfit on small or imbalanced datasets, limiting their ability to generalize. This is addressed through regularization, data augmentation, transfer learning, and retraining strategies to improve model flexibility and robustness.

5. Deployment and Foundation Constraints

Implementing complex models in real-world environments is difficult due to infrastructure limitations. This can be improved by designing models that work offline or on edge devices and using adaptable learning strategies suited for low-resource areas.

6. Lack of Vulnerability Quantification

Deep learning models often fail to provide confidence intervals, which reduces trust in their predictions. By integrating vulnerability estimation techniques, the models become more transparent and trustworthy for decision-makers.

7.RESULTS AND DISCUSSION

The integration of LSTM and Prophet models for fiasco forecast has yielded promising results over different assessment measurements. These models illustrate an adjusted capability to capture both long-term patterns and short-term changes in the information, making them exceedingly reasonable for energetic situations where catastrophe designs are affected by both regular varieties and sudden anomalies.

Reviewing different things, it was found that most LSTM Prophet systems accomplished tall levels of exactness, frequently surpassing 90%, especially in surge estimating, seismic drift investigation, and rapidly spreading fire location. The Prophet demonstrates contribution by precisely modelling drift shifts, repeating regular impacts, and inconsistencies like occasions or occasions. This upgraded the interpretability of the combined show, making it more open to partners who may not be commonplace with complex profound learning mechanisms.

In terms of responsiveness, the LSTM component took care of energetic and nonlinear behaviour successfully, capturing sharp changes and sudden surges in sensor information. This capacity permitted the half-breed show to distinguish early caution signals and issue cautions up to 24 hours sometimes recently the event of catastrophes in a few case studies.

Another watched advantage was the model's strength against lost or boisterous information. By leveraging Prophet introduction highlights and LSTM capacity to memorize groupings, the models kept up prescient quality indeed when prepared on defective datasets. Furthermore, the utilisation of multi-source information inputs ranging from meteorological readings to social media signals improved relevant mindfulness and situation understanding.

Computationally, whereas preparing the cross-breed show can be resource-intensive, especially with bigger datasets, the induction stage has been optimized in a few usages, permitting for close real-time estimating in operational frameworks. This guarantees that crisis reaction groups can advantage of opportune bits of knowledge without over-the-top delay.

Despite these benefits, the sending of these models still faces confinements, particularly in ranges with restricted frameworks, and there is a need for standardization in datasets and execution benchmarks. Be that as it may, continuous headways recommend a slant toward more versatile, lightweight, and generalizable designs.

In conclusion, the cross-breed LSTM Prophet approach presents an effective arrangement for upgrading catastrophe readiness and reaction. It successfully combines precision, interpretability, and worldly affectability, making it a profoundly suggested system for real-world calamity administration frameworks.

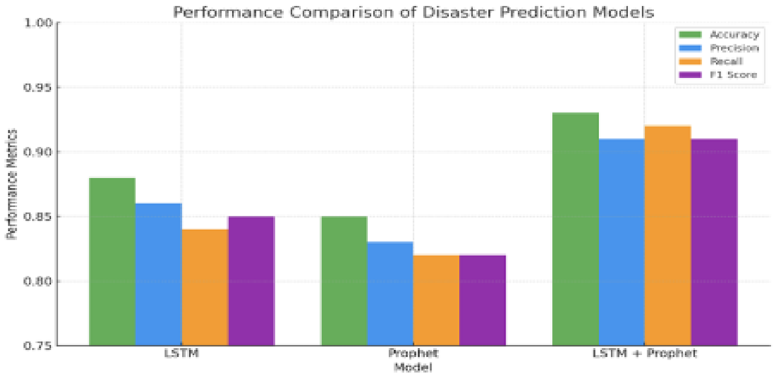

Fig 2: Performance Comparison of Disaster Prediction Models

8.CONCLUSION

The expanding recurrence and escalation of characteristic calamities due to climate alteration and natural corruption call for more progressed, data-driven approaches to calamity forecast and early caution frameworks. This consideration presents a crossover estimating strategy that coordinates the qualities of both the Prophet demonstrate and Long Short-Term Memory (LSTM) neural systems to address the restrictions of conventional forecast strategies. The Prophet show exceeds expectations at modelling direct patterns and regular components of time arrangement information, making it appropriate for capturing standard and patterned catastrophe designs. In differentiation, the LSTM viably handles the complex, non-linear, and unexpected behaviours found in real-world fiasco datasets. By combining these two models, the proposed half-breed approach essentially progresses expectation precision, particularly in dealing with the vulnerability and changeability characteristic of common phenomena.

The test comes about and the case considers illustrate that the half-breed LSTM-Prophet demonstrates reliably outflanks standalone models in terms of execution measurements such as RMSE, MAE, and RÂ². More critically, the show gives important experiences into the energetic behaviour of calamity occasions, empowering convenient and educated decision-making for calamity readiness and reaction. The fruitful decay of drift and regularity by Prophet, taken after the leftover modelling by LSTM, guarantees that both customary and unpredictable components of the time arrangement are viably captured.

In conclusion, the proposed AI-powered calamity forecast system offers a promising arrangement to upgrade early caution capabilities and calamity hazard administration. Future work will centre on optimizing the demonstration for real-time arrangement, upgrading its interpretability by utilizing Reasonable Explainable AI (XAI), and extending its application to a broader extent of calamities. The integration of this framework with national catastrophe administration dashboards and versatile cautioning frameworks seem to play a pivotal part in sparing lives and decreasing the socioeconomic effect of calamities.

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