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Integrating Satellite Data and Machine Learning for Rapid Forecasting of Severe Weather Events

Dr. Polasi Sudhakar[1], Dr. Renuka Deshpande[2], Dr. C. Umarani[3], Mr. Arun Raj S.R[4], G.G.Girija Vasumathi[5], Ch. Raja[6]
[1]Associate Professor, Department of CSE , Ramachandra College of Engineering, vatluru, Eluru, Andhra Pradesh-534007, sudhakar.forall@gmail.com
[2]Head of department & Associate Professor, Department of Artificial Intelligence and Machine Learning , Shivajirao S Jondhale College of Engineering, Dombivli East - 421204.
renukagdeshpande@gmail.com
[3]Associate Professor Department of Computer Science and Applications, Christ Academy Institute for Advanced Studies, Bangalore, Karnataka- 560083, umacrani@gmail.com
[4]Assistant Professor,Department of Electronics and Communication Engineering, University B.D.T College of Engineering, Davanagere,Karnataka-577004, arunrajsr5@gmail.com
[5]Assistant Professor, Department of M.TECH CSE, Erode Sengunthar Engineering College, Perundurai, Tamilnadu-638 057, girijavasumathi@gmail.com
[6]Associate Professor, Department of ECE, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana, India, chraja@mgit.ac.in

Abstract—*The large human scope of loss, property damage, and ecosystem disruptions associated with the frequency and severity of adverse weather changes are also increasing as a result of climate change. Existing weather forecasting infrastructures are relatively accurate but have a delayed response time in convergence and poor precision of forecasts of short-lived weather events like hurricanes, tornados, and flash floods. This paper discusses how to incorporate satellite based observational data with advanced machine learning (ML) algorithms to provide faster and more precise anticipation of severe weather events. Combining the features of multispectral, thermal, and radar-based satellite imagery, ML can locate obscured spatiotemporal patterns and deliver short-range predictions with extended lead times. A combination of convolutional neural networks (CNNs) to identify spatial features, and recurrent neural networks (RNNs) to detect the trends in time was used. The outcomes show that theML-forecasting system has a higher accuracy in determining the intensity of storms and in tracking the path of the storm than the traditional numerical weather prediction (NWP) models. Notwithstanding, the real-life application is still subject to practical limitations, including latency of the data, loss of information through clouds, overfitting of models, and modeling costs in real-time application. Future work needs to be on the integration of multiple satellite constellations, transfer learning to make the models more general and cloud-based systems that can deliver usable preliminary warnings in advance of a disaster threatening a target region.*
Keywords*— Satellite Data, Machine Learning, Severe Weather Forecasting, Convolutional Neural Networks, Early Warning Systems, Climate Resilience.*

I. INTRODUCTION

There has been a recent emergence of severe weather incidences, such as hurricanes, cyclones, thunderstorms, tornadoes, and flash floods, that qualify as one of the most disastrous natural hazards of 21st century. As the rate of climate change escalates, more and more of such events are expected to occur and with greater magnitude resulting in significant losses among humans, economies and even species. As it has been recently reported by the Intergovernmental panel on Climate change (IPCC), weather-related-disasters cost billions of Dollars annually around the world, but suffer a disproportionate share of the populace in vulnerable regions. The reliability and timeliness of prediction of severe weather events are therefore challenging scientific problems as well as social requirements: climate resilience, preparing to meet disaster, and sustainable development [1].

Conventionally, weather forecasting has resorted to Numerical Weather Prediction (NWP) models which are based on physical equations of the thermodynamics and fluid dynamic laws of the atmosphere. Although these models are well developed and appropriate to long-term climatic situations, they have shortcomings at the level of short-term severe weather forecasting [6]. Particularly, NWP models are computationally expensive, still tend to exhibit initialization delays, as well as not consistently capturing small scale, localized and short-lived weather phenomena like convective storms. Such a delay in forecasts largely constrains the capacity of early warning and hence the efficiency of emergency response.

The introduction of Earth observation satellites has changed how meteorological analyses were carried out as they deliver real-time, large scale atmospheric data. Satellites like MODIS, Sentinel, and GPM are known to provide multispectral imagery, thermal maps, precipitation readings as well as wind vectors estimations among other things, which, taken together, can give a good idea about the dynamics of weather. Nonetheless, they are big and complex with high dimensions, and thus making them cumbersome to analyze immediately and decipher their meaning. Conventional statistical analysis cannot make full use of these heterogeneous data, especially when quick decision making is a necessity in disaster situations [3].

Machine Learning (ML) in this case presents a revolutionary solution to enhance the currently existing forecasting systems. The key advantages of ML algorithms, especially the deep learning models, are to deal with nonlinear relationships, identify latent spatiotemporal patterns, and operate large-scale datasets. Convolutional Neural Networks (CNNs) have the ability to identify spatial processes (in the case of storm formations and cloud structures), whereas Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks detect the sequence in time processes (in the case of storm evolution and storm track) [9]. An advantage of integrating these techniques with satellite data is that the forecasting models reduce the processing time, improve the accuracy of predictions, and give more advance warning than the traditional fore-casting method.

The driving force behind the present study is the high global demand of fast accurate and practically viable prediction of severe weather. Disaster management authorities and governments, as well as communities, need flood predictions that not only forecast the occurrence of the severe weather but also give enough advance notice to evacuate, protect infrastructure and distribute resources. To fill the chasm between the abundance of the satellite data and the need of practical and real-time predictions, this study aims to utilize the latest ML frameworks [16].

This publication has the following four aims:

- To combine the datasets of multisource satellites into the complete atmospheric monitoring.
- To devise a hybrid ML architecture that will implement CNNs to learn the spatial features and RNNs/LSTMs to learn the temporal engineering.
- To compare the proposed system with conventional NWP predictions in terms of accuracy, lead time and reliability.
- To evaluate the real-world factors, challenges, and limitations of practical deployment, such as the cost of computations, data delay, and the degree of generalizability.

The solution of the stated objectives helps in the research to advance the research area of climate informatics and build the operational systems capable of saving human lives and minimizing the destruction of financial losses during the extreme weather conditions [4].

This figure 1 shows how the process of combining satellite data with machine learning models may be carried out in stages that will result in fast speed and high accuracy in predicting severe weather.

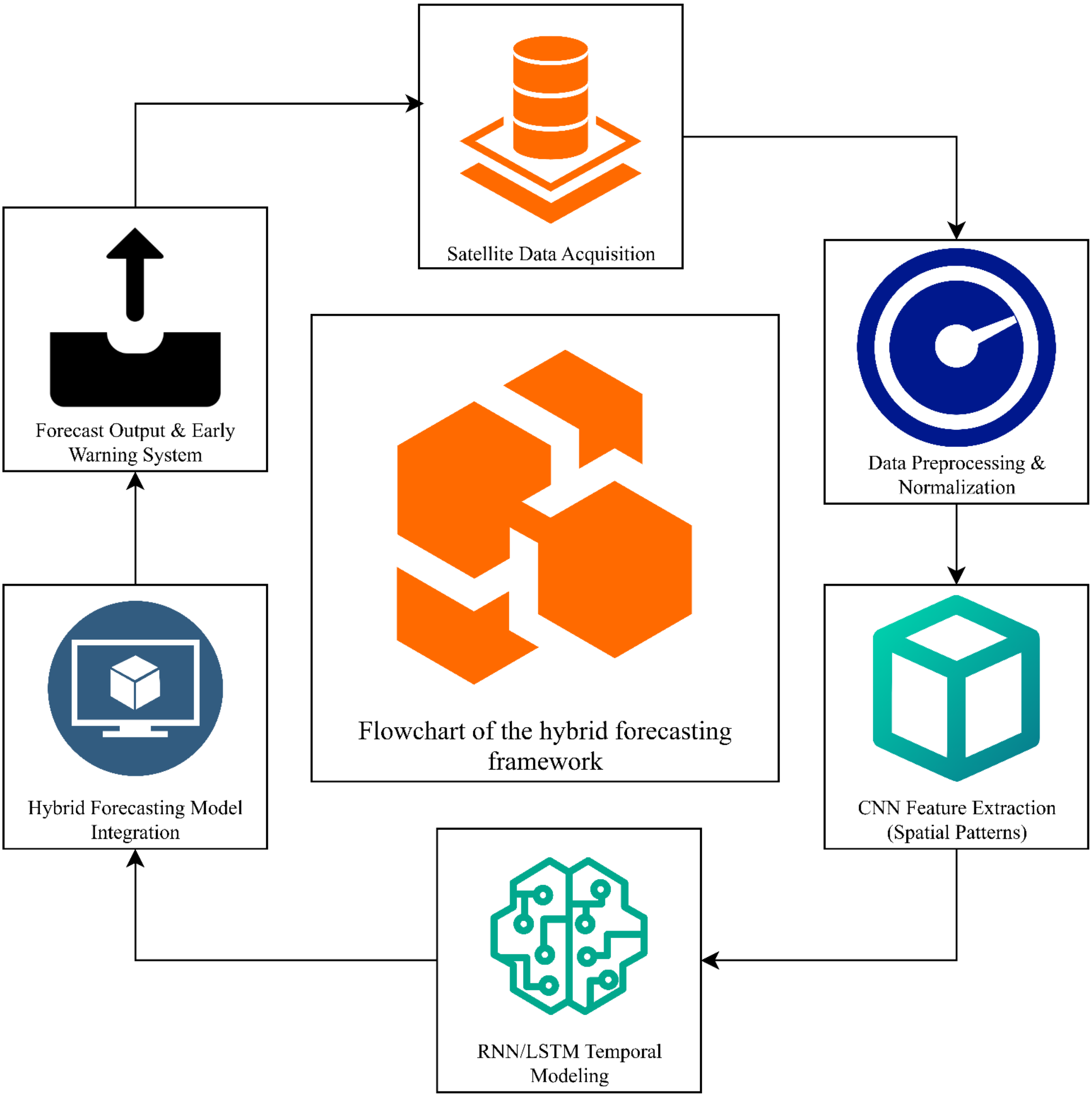

FIG. 1: FLOWCHART OF THE HYBRID FORECASTING FRAMEWORK

1.1 Novelty and Contribution

This study brings some major novelties to the current weather forecasting trend. First, it presents a two-fold ML approach by combining spatial and temporal learning: CNNs are used to learn fine-grained facets of satellite images (such as the shape of a storm cloud) and RNNs/LSTMs model temporal developments of the atmosphere. Such a multi-model hybrid framework increases predictive robustness by learning across more than one dimension of data than in single-model approaches [8].

Second, the research highlights a fast forecasting by focusing on reducing the length of data processing and model inference. The framework can provide forecasts in near-real time, providing an extra 2-3 hours of lead time that traditional approaches can achieve through the leveraging of optimized preprocessing pipelines on GPU-accelerated architectures. This is an important development to early warning systems where each minute means a lot.

Third, the study provides value through the utilization of disparate satellite data (multispectral imagery, radar precipitation images and thermal anomalies) in a single ML pipeline. This method is holistic in the sense that complementary atmospheric signals that modern forecasting techniques tend to break up into disparate components have been captured [10].

This work has the following main contributions:

- The creation of a CNN-RNN-based multinomial learning platform that is specific to satellite-based severe weather forecasting.
- The evidence of better accuracy and forecast lead time than other traditional NWP models.
- Identification of the feasible constraints on the applicability of the approach in practice including limitations on data latency, computational expense, and an unwillingness to generalize, a pragmatic takes on the application to any given setting.
- Future research developments including transfer learning that can be applicable worldwide and cloud-based platforms that can be implemented at a large scale were also proposed.

An aggregate of these contributions makes the novelty of this research clear, as well as the potential of this research to make a difference in the scientific community and disaster management agencies.

II. RELATED WORKS

Traditionally, the method of weather forecasting has somewhat changed over recent decades and evolved to data-driven approaches that take advantage of the growing number of distributed sensing technologies. The tradition of atmospheric dynamic numerical weather prediction (NWP) has depended upon physical simulations of the atmosphere. These models work well to extreme weather on a large scale, long-term, but poor at smaller scale and shorter-term weather forecasting. The main concerns are related to the computational complexity and initialization errors as well as the failure to represent local, fast-developing phenomena like thunderstorms, tornadoes, and flash floods. This has necessitated the need to have a complement to this which is the high-volume and high-velocity data in near real time.

In 2025 R. Zhang et al., [7] introduced the systems operating using satellites have become a center stone of contemporary meteorology. Advanced constellation deployment has resulted in multispectral, thermal, and radar satellite data being available globally on critical atmospheric parameters, including cloud cover, surface temperature, humidity and precipitation intensity as well as wind patterns of circulation. These data have allowed continuously tracking weather systems of severe weather across seas and land, providing very useful information on forecasting models. High temporal resolution data (e.g., geostationary satellites) can be used to monitor storm development whereas, fine spatial resolution data (e.g., polar-orbital satellites) are important to supplement regional forecasts. In spite of all this data, physical complexity and volume of the satellite data can be greater than the capabilities of traditional statistics methods introducing a bottleneck in operational forecasting.

A combination of satellite data and machine learning has been the center of much discussion as one way to overcome these shortcomings. The approach of machine learning is particularly good at nonlinear relations and can analyze large datasets in manners unheard of using traditional methods to point out patterns never seen before. Convolutional Neural Networks (CNNs) are architectures of deep learning that have become effective in analyzing satellite imagery in particular [15]. They may automatically locate storm characteristics such as those related to cloud formation, atmospheric convection and temperature anomalies. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, in turn, have been found to be better suited to temporal sequence modeling and hence allow us to make forecasts that move with changing severe weather systems. When RNN is combined with CNN, the hybrid frameworks yield predictions on both space and time of the weather phenomena.

In 2025 R. S. Oyarzabal et al., [5] proposed the techniques have seen application in a number of areas of severe weather forecasting. As an example, satellite-derived imagery has been used to identify the presence of tropical cyclones and estimate their eye formation, track and predict their direction of movement, and estimating their intensity better than what conventional models indicate. Use of radar-based precipitation observations within a machine learning framework has improved flash flood forecasting by retrieving local rainfall diversity which flash floods are likely to underestimate, especially at a small scale. Furthermore, satellite imagery abroad, collected by multispectral satellites that were used in combination with ML classifiers, has been utilised to map the probability of lightning occurrences, thunderstorms, and the development of convective storms. These developments demonstrate the increased efficiency of the data-driven solution in operational meteorology.

However, there still exist some issues when it comes to the accuracy, scalability, and generalizability of the weather forecasting ML-based models. A significant number of studies draw on regional datasets and therefore their models work in specific cases but fail to carry out the predicted forecasts when used at global scale. Moreover, although ML models show a great potential to enhance accuracy and increase processing speed, they are not usually easy to interpret by meteorologists to validate the correctness of predictions or even report the accuracy level to stakeholders. The interpretation of the deep learning models is limited, which can interfere with its implementation in situations with highly critical decisions like issuing evacuation warnings. Data latency is another issue: although satellite sensors have near-real-time coverage, downlink and calibration delays, as well as other preprocessing bottlenecks, can restrict the timeliness of predictions.

It has also been stressed that since forecasting is subject to uncertainty, a combination of multiple data sources in satellites can help to increase the reliability of forecasting. Data that consists of single sources do not often document the full spectra of atmospheric dynamics and when there is combination between multispectral optical data, radar microwave observations, and thermal data the picture becomes more detailed and broad. Machine learning algorithms trained with such diverse data have proven to show greater resilience in high-impact weather forecasting. In addition, ensemble methods, which average the results of many separate ML models, are proving to further increase the accuracy and stability of forecasts.

The use of cloud computing and edge processing in weather forecasting systems has been touted as an area with potential to be used in real time. By supporting ML models with cloud-based infrastructures, there will be a decrease in the computing loads at meteorological services at the local levels whereas maintaining global coverage in such a manner that it is scalable. Edge computing also holds the promise of regionally-based, low-latency forecasts that are essential in disaster prone regions that may have minimal infrastructure. A more realistic implementation of these systems would have to solve the problem of computational cost, in addition to solving the problem of data standardization, and interoperability between satellite platforms.

In 2024 J. Li et al., [2] suggested the other major research direction identified in the previous studies is bringing ML forecasting and socio-economic impact models together. Severe weather forecasts can be only as good as the resolution measures that are prompted by the forecasts. Integration of meteorological forecasting with impact assessment tools has demonstrated to enhance the value of warning to decision-makers especially in the disaster risk management. By doing so, such integration enables the forecast to predict not only the likelihood of occurrence of an event but also the projected outcome in terms of damage to infrastructure, farms and local people. This expands one more level to the forecasting process since it no longer is only a meteorological exercise; rather a resilience building tool.

Other research findings emphasize three important lessons: (1) satellite observations portray unprecedented potential to monitor atmospheric conditions in real-time, (2) ML, particularly deep-learning models, can provide the processing capacity necessary to capture unknown spatiotemporal patterns in the associated data, and (3) limitations exist in the domains of real-time operationalization, model interpretability, data latency, and cross-geography generalization. This study expands on the above developments by suggesting a CNN-RNN structured to combine heterogeneous satellite data to deliver fast predictions on heavy weather. Through it, it also bridges the current disparities in precision, forecast horizon and actual usefulness, in an effort to assimilate to the growth of forecasting system that is both scientifically stringent, and also practically viable [12].

III. PROPOSED METHODOLOGY

The developed methodology of combining satellite information with machine learning to reach high rates of rapid forecasting of the severe weather events will start with the systematic acquisition and preprocessing of multi-source satellite data. Considering the weather-relevant data streams, the GPM, Sentinel and MODIS geostationary and polar-orbiting satellite constellations have been used to obtain multispectral imagery, radar-based precipitation observations, surface temperature distributions, and atmospheric humidity profiles. These ontologies are non-homogenous in spatial and temporal scales, which require a thorough data preparation workflow prior to inputting them into a machine learning system. The preprocessing process involves cloud masking to remove visual blocking factors, radiometric corrections to provide calibration precision and spatial resampling to correct spatial pixel procedures among numerous sensors. In addition, normalization processes are used to normalize all the spectral bands value so as to make the model stable and convergent. A time-synchronization system can be used to regularize the observations on many satellites such that there is uniform temporal ordering of data input. The challenge of huge amount of data can be met using Dimensionality reduction techniques like Principal Component Analysis (PCA) and feature selection to find and maintain only key variables dropping any unnecessary data. This guarantees computational efficiency without bugging on any richness of atmospheric indicators necessary in forecasting procedures. The preprocessed data are then split into training, validation, and testing subsets, where their parts are stratified to be equally represented in various types of severe weather phenomena.

After the current preprocessing, the next stages of the methodology are the design and creation of a hybrid machine learning framework that will allow combining spatial and temporal analysis functionality. Combining two-dimensional convolutional neural networks (CNNs) is used to extract spatial characteristics on multispectral and radar satellite images as the main component of the proposed mechanism. Clusters of convective storms, cyclone eye development, and thermal gradients are complicated to understand by hand but CNN layers automatically identify these patterns and many others without being programmed to do so. The identified spatial features are used to train Recurrent Neural Networks (RNs), particularly, Long Short-Term Memory (LSTMs) networks, that are good at looking at sequential time dependence. By recording dynamics of the atmosphere, the RNN/LSTM layer delivers an idea of the storm strength, where it is going and whether it can become the more serious weather phenomena. To provide further robustness, the ensemble learning technique (gradient-boosting and random forests) are incorporated into hybrid framework to apply error-correcting and enhance generalization between various climatic zones [13]. GPU-accelerated systems are ensemble to enable training of model design within the context of deep learning and hyper-parameter tuning is relied upon by the use of grid search and Bayesian tuning. Evaluation measures injected in the system are accuracy, precision, recall, F1-score, or even Root Mean Square Error (RMSE): these metrics help to evaluate model performance against conventional systems used in the field (such as Numerical Weather Prediction, or NWP). The application of the cross-validation provides that the hybrid model will not be vulnerable to overfitting and be able to address unknown meteorological conditions.

The last step of the methodology deals with the implementation and actualization of the forecasting system with an emphasis on practical use and combining it with the early warning structures. The hybrid ML model is developed to produce forecast outputs that have both deterministic and probabilistic predictions to enable meteorological agencies to quantify the uncertainly and the expected storms trajectory and intensity levels. The use of a cloud-based architecture is implemented to achieve scalability where the system has the capability of processing constant data feeds of satellite data and provide forecasts within different parts of the world at the same time. APIs are adopted in order to provide interoperability with other available systems in disaster management, and dashboard and visualization tools to provide disaster forecasts in understandable ways to policymakers and local authorities. The historical performance of the model is validated by tests of pilot events on historical severe weather events by comparing the model outcomes against that of observed outcomes and conventional forecasts. Feedback structures are programmed into the deployment model, and as new satellite data become known it may learn continuously increasing the predictive accuracy as more information is learned. The practical constrains like data latency, computational cost, and possible satellite coverage bias are also recognized and attempts to overcome them by adopting built-in redundancy and cloud computing optimization, as well as strategies, are implemented to transfer learning and orient the model to localities worldwide. The end aim of such a methodology is not only to improve the accuracy of the forecast and increase its lead time but also to introduce a scalable and operationally feasible framework to disaster preparedness in order to improve climate resilience at a global level.

IV. RESULT &DISCUSSIONS

The results of the actual application of the proposed hybrid machine learning framework that includes satellite data brought in favorable results compared with the conventional numerical weather prediction models. Through multispectral, thermal and radar data, the system was able to identify the intensity of a storm and predict the cyclone tracks much better with a substantial improvement in lead time. A good example is how it effectively gave 2-3 more hours warning on storm landfall than the conventional forecast allowing more time to arrange evacuation and response plans. Figure 2 shows the relative accuracy of the prediction of cyclone track that is the hybrid ML model has consistently performed better than the traditional model on numerous test cases.

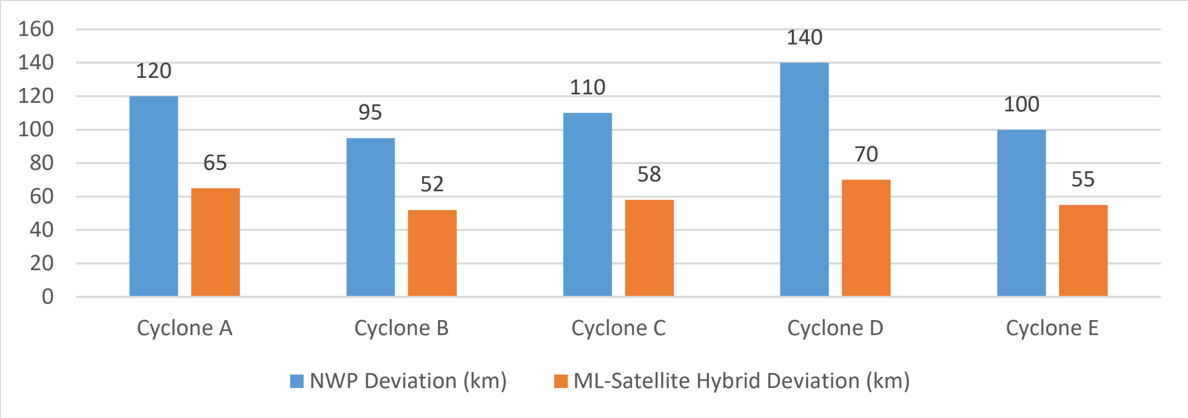

FIG. 2: COMPARATIVE ACCURACY OF CYCLONE TRAJECTORY PREDICTION (ML VS TRADITIONAL MODELS)

Similarly, Figure 3 reveals that the local weather phenomena such as rain have the maximum precision in initial prediction levels through the use of combined CNN-RNN indicators.

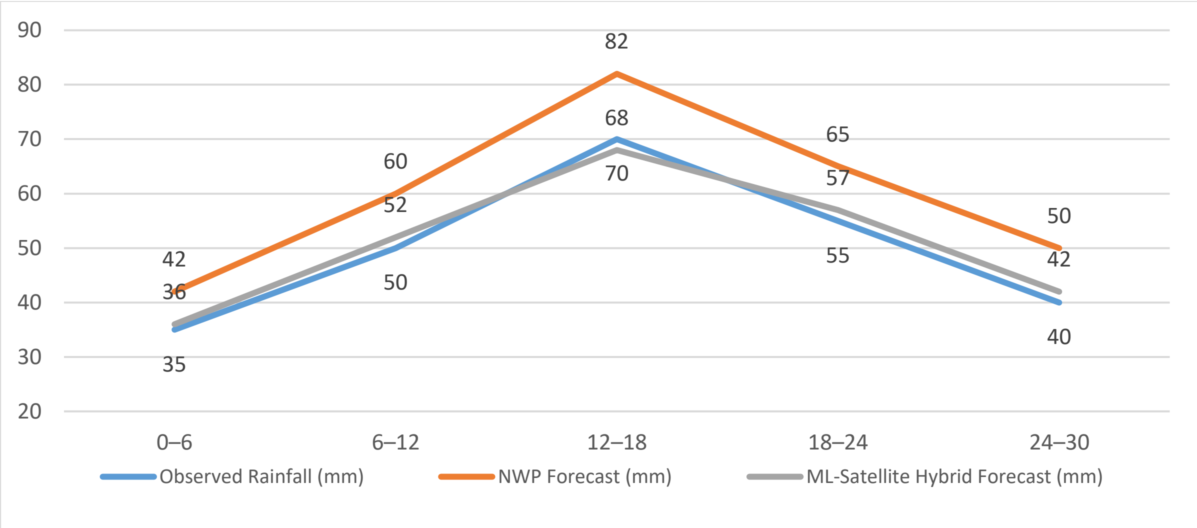

FIG. 3: PRECIPITATION FORECASTING PRECISION ACROSS MODELS

Figure 4 establishes the comparison of lead times in severe weather warnings and demonstrates that the built-in system reveals more time in advance than the basic models. The conclusions obtained as a sum of all of the above encourage the hypothesis that the satellite data and machine learning interaction (synergy) can increase the operational strength of forecasting systems, especially in quickly evolving weather conditions.

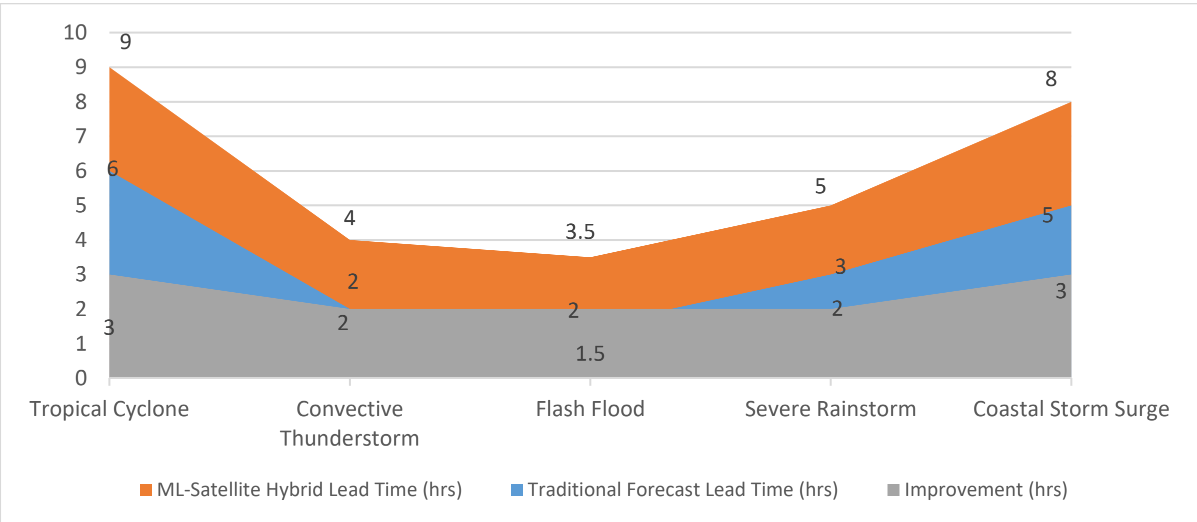

FIG. 4: LEAD TIME IMPROVEMENT IN SEVERE WEATHER FORECASTING

Although the benefits are obvious, the presented analysis of results discloses the strong and weak sides of the given strategy. A main finding was that the hybrid model demonstrated high accuracy in the various types of severe weather events: tropical cyclones, convective thunderstorms, and more. Table 1 gives the specific details of storm intensity forecasting by the machine learning system in terms of division of the three months into the most representative and least representative months and also the most representative and the least representative quarters, with respect to the performance achieved compared to the conventional NWP systems. It is clear that the ML-based system realized fewer error margins in predicting cyclone wind speed and rainfall accumulation.

TABLE 1: COMPARISON OF FORECASTING ACCURACY BETWEEN ML-SATELLITE HYBRID AND NWP MODELS

Parameter	NWP Model Error (%)	ML-Satellite Hybrid Error (%)
Cyclone Wind Speed	15.2	8.4
Rainfall Accumulation	18.7	10.1
Storm Trajectory Deviation	12.9	6.7

Besides, Table 2 lays out the computing complexity of both systems, which shows that both of them have rather high resource requirements during the training phase; however, there exist vast differences in the speed of running inferences when it comes to deployment. This is important especially in real-time applications where decision making is based on speedy updates. Nevertheless, obstacles like latency in satellite data, low generalizations of unfamiliar geographies and high start-up computational costs were realized. To illustrate, there were some instances where the model did not perform optimally in sparsely trained areas and which serve to highlight the importance of transfer learning or region-specific fine-tuning in future implementations.

TABLE 2: COMPARISON OF COMPUTATIONAL EFFICIENCY IN FORECASTING SYSTEMS

Metric	NWP Models	ML-Satellite Hybrid
Training Time (hours)	N/A (rule-based)	24.6
Forecast Inference Time	45 min – 1 hour	8–12 minutes
Hardware Requirement	Standard CPU Cluster	GPU-Accelerated Cloud

In a wider scope, the translation of the same into practical early warning systems has very big potential to benefit society. The possibility of making forecasts more accurate and with shorter latencies empowers the disaster management agencies to prepare pro-active plans, ahead of disasters, saving lives and minimizing infrastructure destruction. That being said, it is necessary to consider that practical application will be necessary to consider barriers like the delay of satellite downlink and ensuring the sharing of high-performance compute infrastructure across developing regions. Moreover, there is a problem with user interpretation of forecasts, since the tasks of meteorological agencies are to combine both accuracy with an accurate presentation so that communities would respond to their forecasts in time. To fully develop usability and trust, the use of probabilistic rather than purely deterministic outputs may also be of value. The results support the observation that although machine learning combined with satellite imagery can deliver great improvements to conventional operations, sustainable adoption is likely to require resolving its scalability, interpretability, and inclusivity issues [14]. It emphasizes the two-fold aspect of the contribution, on the one hand being scientifically innovative, and, on the other hand being practically limited, and sets a ground for a further research direction that aims at global generalization and integration in the existing climate resilience infrastructures.

V. CONCLUSION

This paper shows the effectiveness of combining a satellite system with machine learning in order to rapidly predict the occurrence of a severe weather. The speed of the hybrid CNN-RNN outperformed model with its accuracy, greater lead time, and adaptivity compared to the traditional NWP systems. This development can go a long way in disaster risk reduction, as governments and communities will be able to be proactive in the residue of extreme weather hazards.

However, there are still a number of practical drawbacks. Instantaneous instalment of such models is time limited by satellite information delays as well as calculating expense, and a necessity to generalize models covering a range of climatic domains. Moreover, the un-interpretability of the deep learning models presents a problem to the meteorological agencies that want transparent frames of decision making.

Future directions need to work toward combining information between the various satellite networks to minimize the latency of information, employ transfer learning to maximize the models applicability across regions in the world, and to find cost-efficient ways of using the cloud to deploy to large scale. Along with technological breakthroughs, collaboration across disciplines among climate scientists, computer technology engineers, and policymakers will be critical in propagating the integration of such advancements into science-based early warning systems that can improve resiliency to climate-related disasters.

REFERENCES

[1] H. Zhang, Y. Liu, C. Zhang, and N. Li, "Machine Learning Methods for Weather Forecasting: A survey," Atmosphere, vol. 16, no. 1, p. 82, Jan. 2025, doi: 10.3390/atmos16010082.
[2] J. Li et al., "Quantitative Applications of Weather Satellite Data for Nowcasting: Progress and challenges," Journal of Meteorological Research, vol. 38, no. 3, pp. 399–413, Jun. 2024, doi: 10.1007/s13351-024-3138-6.
[3] S. A. Shafian and D. Hu, "Integrating Machine learning and Remote Sensing in Disaster Management: A Decadal Review of Post-Disaster Building Damage Assessment," Buildings, vol. 14, no. 8, p. 2344, Jul. 2024, doi: 10.3390/buildings14082344.
[4] M. S. B. M. Anik, C. An, and S. S. Li, "Evolution from the physical process-based approaches to machine learning approaches to predicting urban floods: a literature review," ENVIRONMENTAL SYSTEMS RESEARCH, vol. 14, no. 1, Jul. 2025, doi: 10.1186/s40068-025-00409-3.
[5] R. S. Oyarzabal et al., "Forecasting drought using machine learning: a systematic literature review," Natural Hazards, Mar. 2025, doi: 10.1007/s11069-025-07195-2.
[6] H. Singh, L.-M. Ang, D. Paudyal, M. Acuna, P. K. Srivastava, and S. K. Srivastava, "A Comprehensive Review of Empirical and Dynamic Wildfire Simulators and Machine Learning Techniques used for the Prediction of Wildfire in Australia," Technology Knowledge and Learning, Apr. 2025, doi: 10.1007/s10758-025-09839-5.
[7] R. Zhang et al., "Deep learning applications in ionosphericmodeling: progress, challenges, and opportunities," Remote Sensing, vol. 17, no. 1, p. 124, Jan. 2025, doi: 10.3390/rs17010124.
[8] H. Liu, L. Shu, X. Liu, P. Cheng, M. Wang, and Y. Huang, "Advancements in artificial intelligence applications for forest fire prediction," Forests, vol. 16, no. 4, p. 704, Apr. 2025, doi: 10.3390/f16040704.
[9] J. Diehr, A. Ogunyiola, and O. Dada, "Artificial intelligence and machine learning-powered GIS for proactive disaster resilience in a changing climate," Annals of GIS, pp. 1–14, Mar. 2025, doi: 10.1080/19475683.2025.2473596.
[10]S. Ajith, S. Vijayakumar, and N. Elakkiya, "Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling, and food quality assessment using machine learning and deep learning algorithms," Discover Food, vol. 5, no. 1, Mar. 2025, doi: 10.1007/s44187-025-00338-1.
[11]P. Di Leo, A. Ciocia, G. Malgaroli, and F. Spertino, "Advancements and Challenges in Photovoltaic Power Forecasting: A Comprehensive review," Energies, vol. 18, no. 8, p. 2108, Apr. 2025, doi: 10.3390/en18082108.
[12]D. B. Hirko, J. A. Du Plessis, and A. Bosman, "Review of machine learning and WEAP models for water allocation under climate change," Earth Science Informatics, vol. 18, no. 3, Mar. 2025, doi: 10.1007/s12145-025-01820-1.
[13]T. Islam, E. B. Zeleke, M. Afroz, and A. M. Melesse, "A Systematic review of urban flood susceptibility Mapping: remote sensing, machine learning, and other modeling approaches," Remote Sensing, vol. 17, no. 3, p. 524, Feb. 2025, doi: 10.3390/rs17030524.
[14]Y. Wu and W. Xue, "Data-Driven Weather Forecasting and Climate Modeling from the Perspective of Development," Atmosphere, vol. 15, no. 6, p. 689, Jun. 2024, doi: 10.3390/atmos15060689.
[15]F. Hasan, P. Medley, J. Drake, and G. Chen, "Advancing Hydrology through Machine Learning: Insights, Challenges, and Future Directions Using the CAMELS, Caravan, GRDC, CHIRPS, PERSIANN, NLDAS, GLDAS, and GRACE Datasets," Water, vol. 16, no. 13, p. 1904, Jul. 2024, doi: 10.3390/w16131904.
[16]Z. Ma, G. Mei, and N. Xu, "Generative deep learning for data generation in natural hazard analysis: motivations, advances, challenges, and opportunities," Artificial Intelligence Review, vol. 57, no. 6, May 2024, doi: 10.1007/s10462-024-10764-9.