Weather Forecast System using FeedForward Backpropagation Technique

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Abstract: Weather forecasting is an important task in disaster management, especially for a city like Chennai, which is commonly affected by cyclones, heavy rainfall, and heat waves. The proposed study investigates the enhancement of the accuracy and reliability of weather prediction models with the help of the introduction of FeedForward Neural Networks (FFNNs) with the use of Rectified Linear Unit (ReLU) activation functions. Statement: Traditional activation functions like the sigmoid function are not effective activating functions as they suffer from vanishing gradient problems that do not allow deep networks to perform. In order to avoid these complications, FFNNs with ReLU, which allows for high efficiency and sparsity, are used to process large-scale meteorological datasets. The model is trained on historical weather data that is collected and preprocessed, and its performance is evaluated using metrics such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The findings reveal that the proposed approach leads to a notable enhancement in short-term prediction skill, particularly regarding the key physical parameters of temperature and wind speed. The early stopping and dropout layers actually reduce overfitting. These results demonstrate the potential of FFNNs for transforming weather forecasting systems to provide actionable information on extreme weather events risk for disaster management and decision-making in regions exposed to extreme weather events. Our research builds on an expanding body of literature around optimizing neural networks for meteorological applications and suggests areas for further research that could improve robustness and scalability. Citation: Palak Bansal Institute of Higher Education Research, Mandi 174323, India Abstract Accurately predicting the weather remains challenging, leading to injuries and deaths across the globe due to natural disasters.

Keywords: *Weather Forecasting, Disaster Management, FeedForward Neural Networks (FFNNs), Rectified Linear Unit (ReLU), Meteorological Datasets.*

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I. INTRODUCTION

➢ *Problem Statement*

Chennai is a coastal city in the southern part of India, and directly bordering the Bay of Bengal, that also has been experiencing extreme weather—cyclones, heavy rain, and heat waves that are impacting public infrastructure and safety (Climate, 2023). Example 2: Right weather prediction can reduce the risk that revolves around extreme weather events. However, existing weather forecasts struggle with overfitting, a phenomenon in which a model is too tailored to past weather data and does not generalize to new and unseen weather patterns. Artificial neural networks (ANN), in particular types called FeedForward neural networks (FFNN), have shown promise for improved weather prediction due to the ability of these networks to model complex and non-linear relationships in large datasets. Yet another drawback of the FFNN is that they may be subjected to overfitting, which diminishes the potency of the predicted outcome. Aside from the problem of missing data and extreme data, a concern with a suitable activation function, such as ReLU (rectified linear unit), can help against overfitting by making the learning more efficient, and the model can effectively generalize to new data. So, this identified problem illustrated that to develop upon the weather prediction model to feed forward neural networks (FFNN) with activation functions such as ReLU in order to overcome overfitting to forecast the weather of Chennai with higher accuracy.

➢ *Objective*

This research work is, therefore, dedicated to developing a model for accurate weather forecasting over Chennai using feedforward neural networks with appropriate activation functions such as ReLU. The model will also attempt to improve the accuracy of the forecast by overcoming the problem of overfitting so that it generalizes well to new, unseen weather patterns and reliably predicts weather events in the region. This will improve the efficiency

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of forecasting weather changes for better disaster preparedness and mitigation in Chennai.

➢ *Scope*

The present paper is undertaken with the stated objective of developing and carrying out a feedforward neural network for weather forecasting, with necessary emphasis on Chennai in India for the purpose. Major areas captured in the research study result in: Weather Data: We will use historical weather data of Chennai that considers temperature, humidity, wind speed, and precipitation to train and test the FFNN model. Design of Model: The research will develop an FFNN model, specifically focusing on the selection of the best activation functions such as ReLU, which will result in enhancing the model's accuracy and avoiding overfitting. Overfitting Reduction: The challenge of overfitting, common in predictive modeling, will be addressed by the implementation of methods that enhance the model's generalization capability to new, unseen data. Extreme Weather Prediction: Being more specific, the FFNN model will be used to boost the prediction of extreme events like cyclones, heavy rainfall, and even heat waves that form important features of this particular city's climate: Chennai. Performance Evaluation: The model shall be gauged in view of the accuracy of the result in predicting weather patterns and the improvement that it will deliver compared to the traditional forecasting technique in order to check enhancements in the reliability of the forecast. Climate Focus of Chennai: The study will adapt the FFNN model to the particular weather characteristics of Chennai so that the accuracy of the forecasts is enhanced to help the city get prepared for any eventualities arising out of extreme weather conditions. The research shall therefore investigate the use of FFNNs for improving weather forecasts by enhancing their accuracy and overcoming overfitting problems, excluding other more complicated and hybrid techniques of forecasting.

➢ *Highlights*

- Chennai Weather Forecasting: The proposed model is based on an FFNN architecture tailored for predicting extreme weather events that define Chennai's climate, such as cyclones and heavy rainfall.

- Overfitting Mitigation: Techniques are applied to address overfitting, ensuring the model delivers accurate predictions that generalize well to unseen weather conditions.

- Integration of ReLU Activation Function: The ReLU activation function is utilized to enhance the model's efficiency and improve accuracy in handling complex, nonlinear weather variations.

II. LITERATURE SURVEY

The past few decades have seen promising use of artificial neural networks in meteorology, specifically for feedforward neural networks (FFNNs). They have proven to be very effective in the handling of complicated, non-linear relations in weather and climate, far more complex than those that traditional forecasting models are expected to approximate. Today, FFNNs are considered one of the powerful tools of meteorological forecasting that improve predictions with higher accuracy and provide insights into the atmosphere's dynamics. Key studies will be reflected below that illustrate FFNN's role in many applications of meteorology, starting from chaotic system modeling to intensity prediction of a tropical cyclone, short-term weather forecasting, and climate projection.

Some of the significant hurdles to applying FFNNs to meteorological problems come from their tendency to overfit, particularly if they are trained on chaotic systems, like atmospheric dynamics. In a paper published in 2019, Scher and Messori attacked this problem with Lorenz models, which simplifications of weather patterns. They discovered that overfitting may be effectively controlled by early stopping during training. This method improved the ability of the FFNN to generalize to new, unseen data, which is essential in predicting weather conditions outside the available historical data. In weather forecasting, new conditions are always arising, and the capability of FFNNs to make accurate predictions in regions of the data space where no information exists is a major strength.

FFNNs have also been promising in the prediction of extreme weather events, such as tropical cyclones. In a study that appeared in Weather and Forecasting in 2019, researchers looked at using FFNNs to better forecast the strength of tropical cyclones, focusing on the often-difficult task of predicting rapid intensification-an event where traditional models have been frequently known to fail. By merging the HWRF model with cyclone data, FFNNs made a more precise forecast of how quickly a cyclone would intensify than their traditional counterparts. This is important as it will enable accurate forecasting of rapid intensification for minimizing the impact of such powerful storms on coastal populations. The work is a demonstration of the capability of FFNNs to model complex, non-linear relationships between various meteorological variables, thus offering an increase over the traditional methods of forecasting.

Machine learning techniques integrating the traditional numerical weather prediction (NWP) models have also gained momentum recently. A 2024 research work combined WRF with a type of FFNN known as Backpropagation Neural Networks, or BPNNs. In this hybrid model, referred to as WRF-BPNN, the strengths of both approaches are brought together.

The WRF model, whose detailed simulations of atmospheric processes act as the back bone of the system, adds a layer of intelligence from the BPNN by learning the complex patterns that exist in data. This resulted in enhanced forecasting accuracy, and thus it can be seen how FFNNs can complement traditional numerical models. The combination of these two approaches indicates a promising future for weather forecasting, where machine learning and conventional methods are combined to improve the outcome of predictions.

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FFNNs have also been successful in short-term weather forecasting. A 2022 study showed that FFNNs could reduce forecasting errors by 20% to 30% when predicting temperature, wind speed, and precipitation. Although the improvement over traditional methods like multiple linear regression was significant, the study also noted that the quality of the input data, the size of the training sample, and the forecast lead time all played important roles in determining the model's performance. This implies that although FFNNs may really boost the predicting accuracy, they are not all-in-one packages. The success of FFNNs in short-term forecasting relies on several points to be optimized, such as data quality and training strategies.

FFNNs have also been used for energy-related weather forecasts, such as for prediction of the wind speed. Accurate prediction of wind speeds is important because the renewable energy sector is particularly sensitive to fluctuations in wind regimes, which can heavily influence energy production and grid stability. In 2021, for the first time, a novel FFNN model was developed that showed better results than traditional models. The model was very useful in a sector where small inaccuracies in wind speed predictions can have large implications for energy production and distribution. This study highlights the potential of FFNNs to provide more reliable forecasts in the renewable energy sector, offering a tool for better planning and decision-making in the face of variable wind patterns.

Air temperature prediction is yet another area where FFNNs have performed significantly well. A study from 2020 shows how a deep learning model, such as FFNN, can correctly predict air temperature for several different forecasting horizons. This flexibility of the FFNN helps it in short-term as well as long-term predictions of temperature, which can be used in a variety of applications, from daily weather forecast to seasonal and even climate projections. With these capabilities, the FFNN will be able to adapt to several types of meteorological data; hence, their future prospect in meteorology is quite hopeful.

Though extensively studied and widely applied in various meteorological problems, other highly advanced neural networks, such as LSTM networks and CNNs, are also researched. While LSTMs are especially well-suited for processing sequential data with temporal dependencies, a 2019 rainfall prediction study noted that FFNNs could still be effective for some applications, particularly when computational efficiency is a priority. Additionally, a 2022 study introduced deformable CNNs for large-scale atmospheric circulation predictions, indicating the increasing use of machine learning in meteorology. While CNNs are more commonly applied to spatial data processing, their ability to enhance weather forecasting complements the strengths of FFNNs, so hybrid approaches could be very useful.

In summary, FFNNs have been shown to be a valuable tool in meteorological forecasting, providing improvements in accuracy across a wide range of weather prediction tasks. From predicting the intensity of tropical cyclones to improving short-term weather forecasts and optimizing wind speed forecasts, FFNNs have proven to be able to capture the complex, nonlinear relationships inherent in atmospheric dynamics. In addition, the integration of FFNNs with traditional numerical weather models has also been promising, improving forecasting performance by combining the strengths of both approaches. Despite these problems, including overfitting and model optimization, the research is increasing in number regarding FFNNs in meteorology, so it can be assumed that these models will be further developed and become increasingly crucial for enhancing weather forecast accuracy and reliability. When machine learning algorithms advance, then the combination of traditional forecasting methods with modern neural networks has the greatest potential to revolutionize the future of meteorological science.

III. RELATED WORK

A. ANN Approach:

We present a neural network approach to weather prediction. The Backpropagation Neural Network (BPN) method has the benefit that it has been used for function approximation. Backpropagation computes the gradient of the error of the network with respect to its tunable weights, which can then be used in a stochastic gradient descent algorithm to adjust the weights of the network in a direction that will reduce the error. BPN is the multilayer feed network. It consists of an input layer, an intermediate hidden layer, and an output layer.

- *Forward Pass:*

Inputs are provided to the input layer, processed through activation functions in the hidden and output layers based on the weights assigned across the layers. The predicted output is compared with the target output to calculate the Mean Squared Error (MSE).

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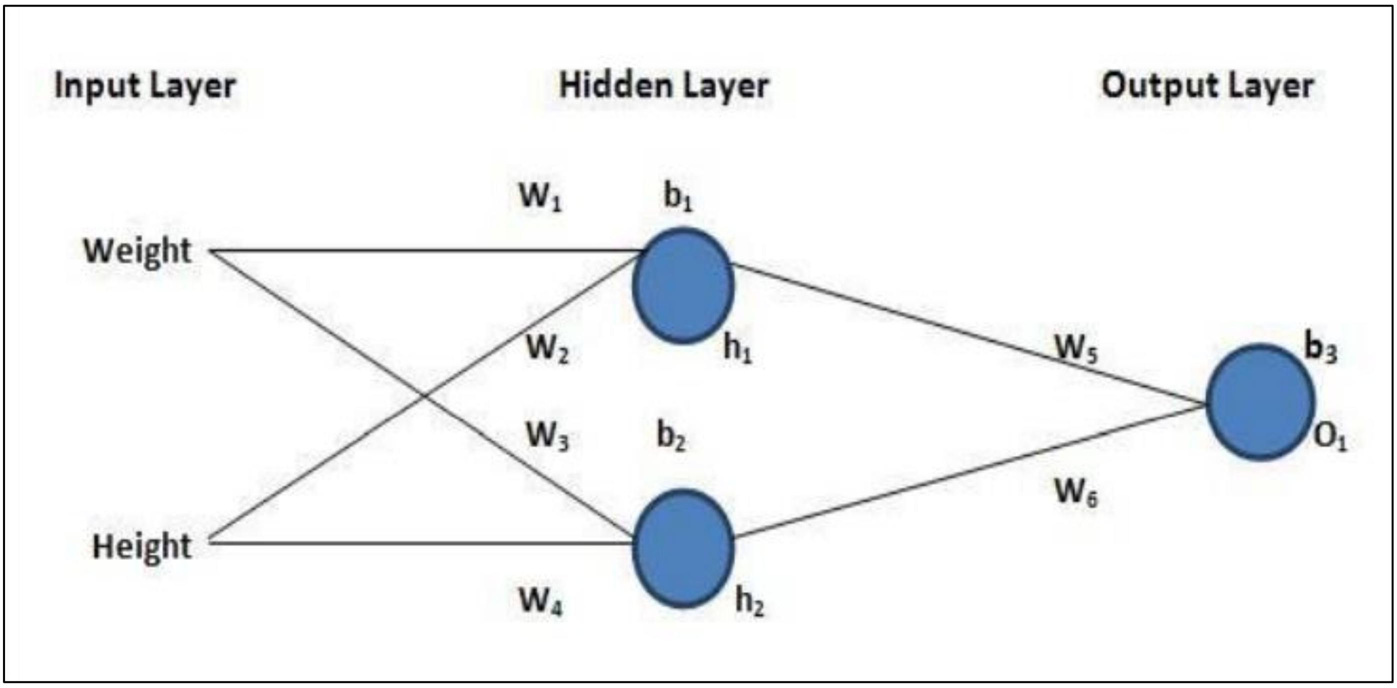

Fig 1 Artificial Neural Network.

➢ *Backward Pass:*

Error, which is the difference between the predicted output and the actual output, is back-propagated through the network to optimize the weights and biases. Let's define: MSE = Mean Squared Error Formula:

$$MSE = (PredictedOutput - ActualOutput)^2 \quad (1)$$

In addition, gradients are calculated via the chain rule to know what weight and bias adjustment will minimize error in the next run. This is what the backward pass does for each layer to allow the network to learn and improve its predictions. Backpropagation Requiring Activation Functions to Provide Derivatives Vanished Gradient Problem for Large or Very Small Inputs: Clearly, the vanishing gradient problem is not an issue in ReLU. Now that we have a little more understanding of what an activation function is, let's see how popular activation functions like Sigmoid and ReLU differ from each other: This paper compares the analysis of the sigmoid & ReLU activation function in feedforward backpropagation neural networks.

➢ *Sigmoid Function:*

Produces values in the range [0, 1], which is ideal for tasks that need a probabilistic output, like binary classification. But it has the vanishing gradient problem that makes learning slow in deeper networks.

➢ *ReLU Function:*

Preferred by deep learning for its simplicity and avoidance of the vanishing gradient challenge. It encourages sparse activation, which allows training to be faster and more efficient. Although the ReLU performs better, it suffers from the "dying ReLU" problem, leading the neuron to do nothing.

➢ *Steps Involved in Implementing the Research:*

- *Step 1: Gather Historical Weather Data:*

Gather historical weather data from reputable sources, like national meteorological organizations or open data repositories. Preprocess the data: handling missing values, normalize features, and convert categorical variables to numerical formats. Divide the dataset into training, validation, and test datasets to assist in an unbiased evaluation of the model performance.

- *Step 2: Training the Neural Network:*

Train using backpropagation with optimizers like Adam or Stochastic Gradient Descent (SGD). Tune hyperparameters (learning rate, batch size, epochs, etc. either through trial and error or grid search. Use early stopping to prevent overfitting during the training process.

- *Step 3: Performance Evaluation:*

Without the taste of validation set evaluation, how can you tune parameters during training? Evaluate test-sample performance of the final model using Mean Squared Error (MSE), Mean Absolute Error (MAE), or Root Mean Squared Error (RMSE). Now contrast the results with benchmarks from traditional statistical models or alternative machine learning approaches.

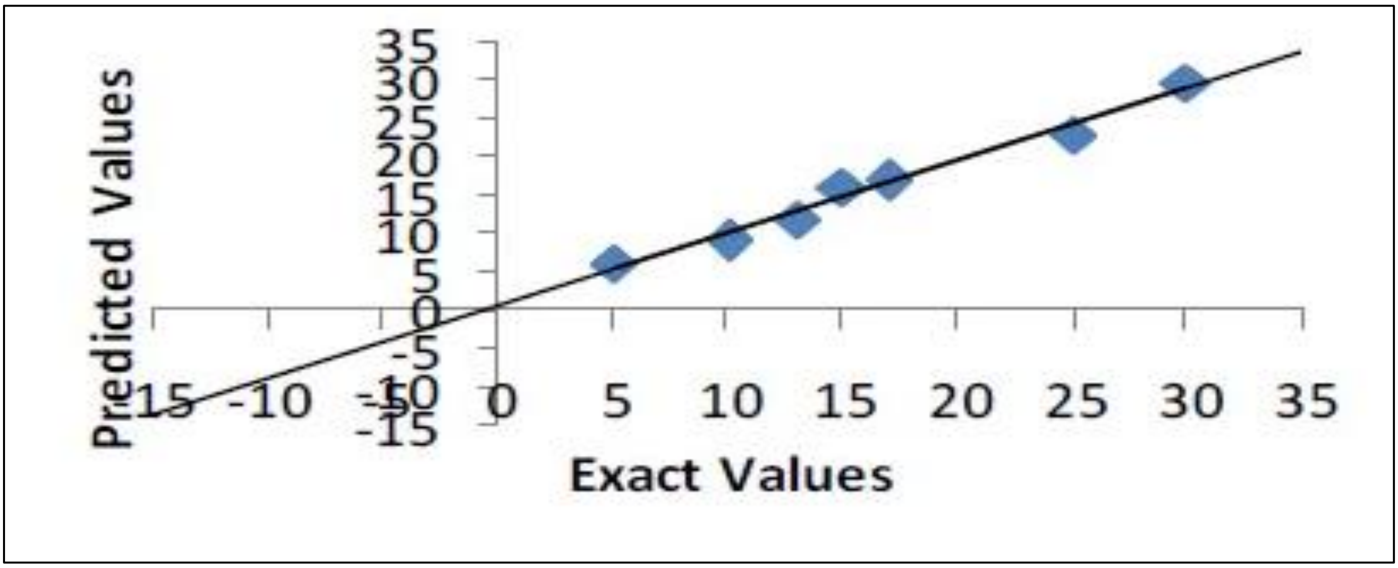

Fig 2 Graph between the Actual and Predicted Value.

➢ *Model Development:*

- Select the FFNN architecture, determining the number of layers and neurons per layer, and using the ReLU activation function for hidden layers.
- Incorporate additional layers or dropout mechanisms to reduce the risk of overfitting.
- Define the output layer according to the forecasting task, such as using a single neuron with a linear activation function for predicting continuous outputs like temperature.
- Model Optimization and Iteration
- Experiment with adjustments to the FFNN architecture, such as adding more layers or leveraging advanced ReLU variants like Leaky ReLU, to boost performance.
- Address challenges like overfitting or inactive neurons through iterative improvements.
- Deployment and Application
- Deploy the trained model within a real-time weather forecasting system.
- Integrate the model into user-friendly interfaces tailored for meteorological experts or public users.

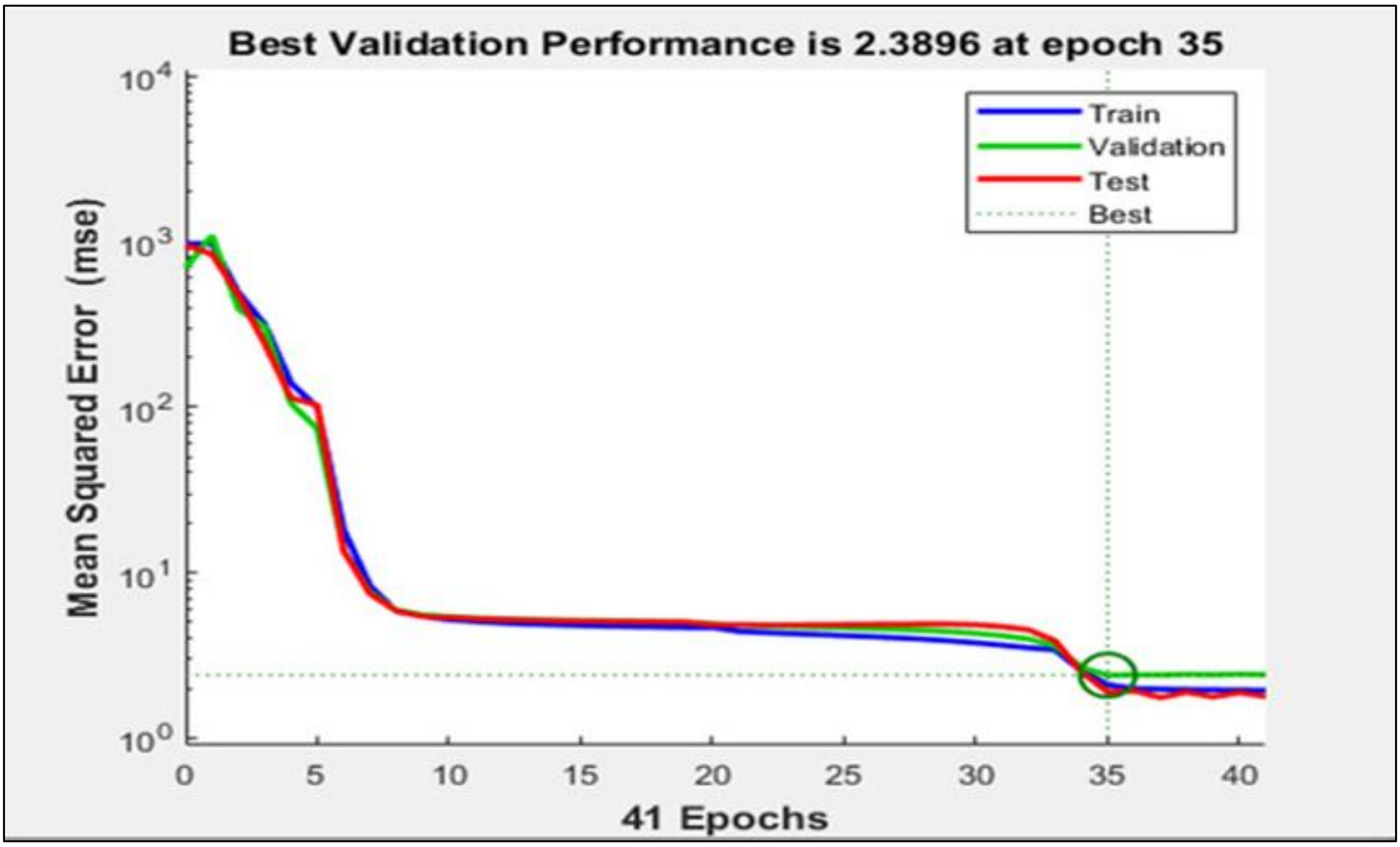

Fig 3 Validation Graph between the Number of Epochs and Mean Squared Error.

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IV. FUTURE WORK

While FFNNs have been adopted in weather forecasting and other fields using activation functions such as Sigmoid and ReLU, many challenges remain to be addressed. The first point is that although ReLU has emerged as the dominant activation function in deep learning, it is subject to the so-called "dying ReLU" problem, where neurons become completely inactive. Even though alternatives like Leaky ReLU and Parametric ReLU are suggested, these changes are poorly optimized and seldom examined on a spectrum of weather forecasting situations. Finally, FFNNs, while they can improve prediction accuracy in some cases, tend to overfit areas of the dataset they are trained on, an issue that is exacerbated in complicated, noisy datasets such as weather data. Most existing work in this area has focused on developing solutions to overfitting the small, idealized datasets by which these models are trained, leaving a sizable amount of work remaining to be done in scaling these models to large-scale, real-world weather datasets. Finally, many previous works consider FFNNs in isolation, ignoring hybrid models or incorporation with other ML techniques, providing a performance and generalization boost. Limited research has been conducted in optimizing FFNN with new exciting advanced activation functions, especially like ReLU, for regions and dynamic weather conditions like Chennai. Filling such gaps can potentially improve the accuracy, scalability, and robustness of FFNN-based weather prediction models for real-time, reliable weather forecasts for areas that are prone to extreme weather events.

V. CONCLUSION

The importance of activation functions in FFBNNs by comparing Sigmoid and ReLU. Sigmoid is useful at the output layer where the task is binary classification but not for deep networks due to its vanishing gradient problem. Because ReLU is very computationally efficient and helps prevent the vanishing gradient problem, it is the default choice for hidden layers in all but the most cutting-edge deep learning applications. However, despite its advantages, ReLU is not without its problems, such as the 'dying ReLU' problem, and this remains an area of continuing research. Neural networks trained using an optimizer based on ReLU variants may perform much more consistently for a variety of applications.

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