ESP Journal of Engineering & Technology Advancements (ESP-JETA)
ISSN : 2583-2646
Special Issue

Enhancing Temperature forecasting using DL approach

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Abstract*— This research is about the forecasting of temperature of LSTM networks in the time ranges of short-term, medium-term, and long-term with the addition of white noise for comparative purposes. Observational actual temperature data collected is analysed to see how well the LSTM models perform in terms of precision, robustness and computational efficiency for the different forecast durations. It also looks into how much noise affects precision, contrasting the BWT to baseline white noise method. Experimental demonstrations enable visualization of LSTM networks predictions based on the temperatures in different timeframes. Also, the paper does a broad performance comparison of LSTM against the other baseline methods, which leads to the produced knowledge on the effectiveness of LSTM in the real-life forecasting tasks. As such these finding form the basis for developing sound temperature forecasting systems that incorporates beyond the scope of Agriculture, Energy management, and weather the prediction.

I. INTRODUCTION

Artificial intelligence (AI) aims to emulate human-level intelligence in machines. In computer science, AI refers to the study of "intelligent agents," which are objects capable of perceiving their environment and taking actions to maximise their chances of achieving specific goals. Machine learning (ML) is a field that focuses on the development and application of methods capable of learning from datasets. ML finds extensive use in various domains, such as speech recognition, computer vision, text analysis, video games, medical sciences, and cybersecurity.

Deep learning (DL) is a subset of machine learning that excels at processing unstructured data. Currently, deep learning methods outperform traditional machine learning approaches. Deep learning models draw inspiration from the structure and functionality of the human nervous system and brain. These models employ input, hidden, and output layers to organize processing units. Within each layer, the nodes or units are interconnected with those in the layer below, and each connection is assigned a weight value. The units sum the inputs after multiplying them by their corresponding weights. Figure 1 illustrates the relationship between AI, ML, and DL, highlighting that machine learning and deep learning are subfields of artificial intelligence.

The objective of this research is to provide an overview of various deep learning models and compare their performance across different applications. Section 2 discusses the different deep learning models, including Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Generative Models, Deep Reinforcement Learning (DRL), and Deep Transfer Learning. In Section 3, we conduct experiments and analyze six deep learning models, namely Convolutional Neural Networks (CNN), Simple Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Bidirectional LSTM, Gated Recurrent Unit (GRU), 1 and Bidirectional GRU, using three datasets. Finally, Section 4 concludes the paper

II. RELATED WORK

The weather is a continuous, dynamic, multi-dimensional and non-linear process. Many have researched this topic and developed a number of methods to predict the weather. Until now the best forecasting depends on the mathematical simulations. These are based on generative techniques that obtain the atmospheric dynamics sampled by means of physical simulations. On the other hand, statistical and data-centric approaches also enabled numerous machine

learning models to be developed to date. Chen et al. developed a time-invariant temperature prediction method using fuzzy time series modelling that achieved very good performance where the data is represented in linguistic values.

Due to the learning ability from the historical data of the neural networks, NN got special attention from the researchers, namely the recurrent neural networks for its adaptive nature with time-series data. Therefore researchers utilised the advantage of RNN such as Hong provided a recurrent support vector regression model with chaotic particle swarm optimization technique. In addition, genetic algorithms and ensemble learning for time series forecasting also showed promising performance. In recent years with the advent of deep learning techniques, model performance increased even further. Liu et al. developed a deep neural network-based feature representation model which mainly uses stacked auto-encoder to build the DNN and support vector regression for prediction. They also showed that with the availability of big data, training with the same technique can result even better for time series forecasting. A similar approach also provided in the literature by Hossain et al. which uses the stacked denoising auto-encoders to build a deep network. It is evident from this literature that the air temperature forecasting from multiple related weather variables shows much better performance than historical data of temperature alone. Implementation of Long-Short Term Memory units in the deep neural networks made the forecasting task much easier. LSTM is a special kind of Recurrent Neural Network (RNN) that is capable of learning the long term temporal dependencies in sequential data. A. Zaytar implied a basic LSTM network of two-layered LSTM with fully connected hidden layers of 100 neurons in their research of Sequence to Sequence Weather forecasting with LSTM which showed quite good performance. Followingly, a similar approach has been taken by Hewage et al. using three stacked LSTM layers with basic dense layers in their research that show better performance than the most widely used WRF model. For task-specific uses, the evolution of LSTM got incremental results. Such that, for Wind Power prediction, Maximilian Du proposed a modified LSTM unit with an additional hyperbolic tangent added to the structure greatly increased the accuracy of wind power prediction. Due to the feature representation ability of auto-encoders researchers combined the LSTM network which learns the temporal patterns much better in a generalised fashion. In terms of different autoencoders for feature representation ability, the variational auto-encoders have shown stable and effective performance than traditional auto-encoders.

III. PROPOSED METHODOLOGY

Our proposed model for temperature forecasting leverages a hybrid approach that combines the strengths of LSTM networks for capturing temporal dependencies with statistical methods for enhancing accuracy and robustness across different forecast horizons. The model architecture consists of two primary components: a one-step prediction model optimized for short-term forecasts and a multi-step forecasting model tailored for long-term predictions.

1. One-Step Prediction Model:

- *Input Data: In the one-step prediction model, the input data includes historical temperature observations as well as relevant meteorological variables such as humidity, pressure, wind speed, and solar radiation. Additionally, temporal features such as day of the week, time of day, and seasonal indicators are incorporated to capture cyclical patterns in the data.*

- *LSTM Architecture: The Long Short-Term Memory (LSTM) network architecture is designed to process sequential input data and learn the underlying temporal dependencies. It typically consists of multiple LSTM layers followed by dropout layers to prevent overfitting and improve generalization. The LSTM layers allow the model to retain information over time, enabling it to capture short-term patterns and dynamics in the temperature data.*

- *Output Layer: The output layer of the one-step prediction model generates the forecasted temperature value for the next time step. This output represents the predicted temperature at a specific future point in time, typically within hours or days depending on the granularity of the forecast.*

- *Training Procedure: During the training phase, historical temperature data is split into training, validation, and test sets. The model is trained using backpropagation through time (BPTT), a variant of backpropagation specifically designed for sequential data. The training process involves minimizing a loss function, such as Mean Squared Error (MSE), by adjusting the weights of the LSTM layers through gradient descent optimization algorithms like Adam or RMSprop.*

- *Evaluation Metrics: The performance of the one-step prediction model is evaluated using various metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and correlation coefficient (Pearson's r) between predicted and actual temperature values. These metrics provide insights into the accuracy and reliability of the model's forecasts compared to ground truth observations.*

2. Multi-Step Forecasting Model:

- *Input Data: Similar to the one-step prediction model, the multi-step forecasting model utilizes historical temperature observations and meteorological* *variables as input features. In addition, lagged temperature values from previous time steps may be included as inputs to capture temporal dependencies over longer forecast horizons.*

- *LSTM Architecture: The architecture of the multi-step forecasting model extends the one-step prediction model to incorporate a sequence-to-sequence LSTM framework. This framework enables the model to generate multiple future temperature predictions over an extended forecast horizon, spanning days to weeks or even months. The LSTM layers are designed to capture both short-term fluctuations and long-term trends in the temperature data.*

- *Output Layer: The output layer of the multi-step forecasting model generates a sequence of forecasted temperature values spanning multiple time steps into the future. These predictions represent the expected temperature values at successive points in time, providing a forecast horizon tailored for long-term planning and decision-making.*

- *Training Procedure: Similar to the one-step prediction model, the multi-step forecasting model undergoes training using historical temperature data. The training process focuses on capturing longer-term trends and seasonal variations in the data, ensuring that the model can make accurate predictions over extended forecast horizons.*

- *Evaluation Metrics: The performance evaluation of the multi-step forecasting model involves assessing the accuracy and consistency of predicted temperature sequences against actual observations. Metrics such as MAE, RMSE, and Mean Absolute Percentage Error (MAPE) are used to quantify the discrepancy between predicted and observed temperature values, providing insights into the model's effectiveness in long-term forecasting scenarios.*

3. Hybridization and Ensemble Techniques:To further enhance forecast accuracy and robustness, the proposed model may incorporate hybridization techniques such as:

- *Combining LSTM Predictions with Statistical Models: This approach involves integrating the predictions generated by the LSTM models with forecasts from traditional statistical models, such as autoregressive models or exponential smoothing. By combining the strengths of both approaches, the hybrid model aims to improve forecast accuracy and reliability across diverse forecast horizons.*

- *Ensemble Methods: Ensemble methods, such as model averaging or weighted blending, can be employed to combine multiple forecasts generated by different models or model configurations. By aggregating the predictions from individual models, ensemble techniques mitigate the limitations of individual methods and produce more robust and accurate forecasts.*

To further enhance forecast accuracy and robustness, our proposed model may incorporate hybridization techniques such as combining LSTM predictions with statistical models (e.g., autoregressive models, exponential smoothing) or ensemble methods (e.g., model averaging, weighted blending). By leveraging the complementary strengths of different forecasting approaches, the hybrid model aims to mitigate the limitations of individual methods and provide more reliable temperature predictions across diverse forecast horizons.

Our proposed model for temperature forecasting integrates LSTM networks with statistical methods in a hybrid framework tailored for short-term and long-term predictions. By combining advanced deep learning techniques with traditional forecasting approaches, the model strives to achieve superior performance, scalability, and interpretability, contributing to the advancement of weather prediction systems and supporting informed decision-making in various sectors.

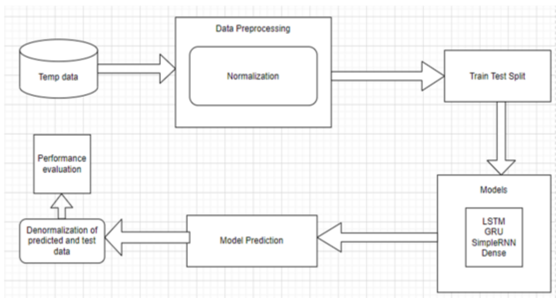

Fig 2: High-Level Overview of the Enhancing Temperature forecasting

V. CONCLUSION

In this paper, we introduced Adaptive Knowledge Transfer with InceptionV3 (AKTWI), a novel approach aimed at accurately identifying and classifying corn leaf diseases. We embarked on our journey by conducting a comprehensive review of existing neural network architectures, meticulously analyzing their strengths and weaknesses. Subsequently, we presented a detailed discussion of our proposed model, providing a step-by-step explanation to facilitate potential re-implementation by fellow researchers.

To validate the effectiveness of our approach, we established a robust experimental setup, detailing system specifications, hyperparameters, and data preprocessing techniques. Leveraging a dataset comprising 3952 images, each with dimensions of 299 × 299 pixels, we embarked on our quest to unveil the potential of AKTWI in corn leaf disease classification.

The outcomes of our experimentation were indeed remarkable. Our proposed AKTWI model achieved an impressive accuracy rate of 97% in differentiating healthy corn leaves from three prevalent diseases: Blight, Common Rust, and Gray Leaf Spot. This stellar performance was made possible by employing data augmentation, a popular data normalization technique, which facilitated the creation of diverse training data variations, thus enhancing the model's generalization capabilities.

A comparative analysis of AKTWI's performance against established CNN architectures underscored its superiority in corn leaf disease classification. Notably, our approach autonomously learned to effectively recognize disease patterns directly from images, surpassing conventional machine learning techniques in terms of accuracy and efficiency.

Building upon these promising results, we charted a forward-looking trajectory for our research, focusing on two key areas of enhancement. Firstly, we aim to expand the capabilities of our model by incorporating additional types of corn leaf diseases, thus broadening its scope and applicability in real-world scenarios. Secondly, we intend to explore optimization strategies aimed at reducing model parameters and computational requirements, ensuring scalability and efficiency in deployment.

Furthermore, we envision a potential future application of our research in the development of a mobile application for on-site corn leaf disease identification. By harnessing the power of AKTWI in a portable and user-friendly format, we aim to empower farmers and agricultural practitioners with timely and accurate insights, facilitating proactive disease management and ultimately contributing to the sustainability and productivity of agricultural systems.

In conclusion, our research represents a significant step forward in the domain of corn leaf disease detection, showcasing the potential of deep learning techniques, specifically AKTWI, in addressing critical challenges in agriculture. Through rigorous experimentation and forward-looking planning, we aspire to continue pushing the boundaries of innovation, ultimately making meaningful contributions towards ensuring food security and sustainability in a rapidly evolving world.

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