AgriCastNet: A Unified Deep Forecasting Framework for Smart Greenhouse Microclimates

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***Abstract*—Greenhouse climate control is becoming increasingly important as climate variability increases, especially in various agro-climatic zones. However, fault tolerance is often a problem, especially in current models that tend to fail because they are sensitive to sensor failure, lack generalization ability, and have extremely high computing requirements. This study proposed a forecasting framework to improve fault tolerance and adaptive learning capabilities by incorporating Climatic Influence Indicators (CII) incorporated with more complex deep learning models to accurately and rapidly forecast greenhouse micro-climate. We utilized a multivariate greenhouse dataset, which consisted of temperature, humidity, CO_2 levels, radiation, and water uptake. The CII layer uses embedded temporal importance from input signals in order to improve the reliability of the model in the event of a sensor failure. A review of literature saw research performed on LSTM, GRU models; however, very few papers approached the dual problems of fault tolerance and ease of deployment. Results suggest some mildly successful outcomes, including TCN: 98.89%- PLSTM: 94.86%- XGBoost: 99.59%- TFT: 98.16%, and CNN + BiLSTM: 99.67%.**

***Index Terms*—Greenhouse climate prediction, climatic influence indicators, fault-tolerant forecasting, deep learning, CNN-BiLSTM, PLSTM, XGBoost, Temporal Convolutional Network (TCN), Temporal Fusion Transformer, sensor resili-ence, K-Fold cross-validation.**

I. Introduction

In the current world of agricultural production, greenhouse farming is proving to be a smart and reliable way to produce food, during a time of the most unpredictable climate [3]. These protected environments allow farmers to more precisely maintain constant growing conditions, regardless of the weather conditions outside. Unfortunately, it is almost impossible to control the full number of environmental conditions in greenhouses, including temperature, humidity, CO_2 concentrations, and sunlight. The parameters are continually changing and responding to the indoor plants and the outdoor weather environments. This situation becomes more complex when greenhouses are used in many climate zones, which differ considerably with regard to the various environmental regimes [1], [6]. Because of this situation, it is difficult for one model to always produce good quality results in all locations [4]. The emergence of deep learning offers new avenues to consider when developing a solution to the problem outlined above, particularly with LSTM and GRU models that are specialized in processing time series data [2], [3], [5]. However, they come with their limitations, like a high computational power requirement and information provided by faulty sensors [7]. To leverage the benefits of deep learning models on this problem, the solution we propose is a hybrid forecasting framework that uses Climatic Influence Indicators (CII) combined with effective deep learning models to enhance flexibility and adaptability, reduce the impact of faulty sensors, and improve greenhouse microclimate forecasting accuracy [3], [9].

In this study, we used a real-time multivariate greenhouse dataset that captures key environmental variables: temperature, humidity, CO_2, radiation, and water uptake. The dataset is collected across different agro-climatic zones, thus allowing the models to be trained and validated using a wide variety of environmental forms, which is important when the temporal sequences will be used for prediction, where climatic behaviour is variable and uncertain [1], [2]. This architecture can incorporate space features (CNN) and sequential learning (BiLSTM), providing an ample amount of temporal information and complete structural variability to face the uncertainties of multi-sensor examples across all predicted zones with reductions in the accuracy of one or more individual sensors [3], [4].

We analyzed different forms of models for predicting greenhouse climate. The CNN + BiLSTM model provided the best accuracy, when a BIA was 99.67%. XGBoost was very close, at 99.59%. TCN and TFT provided similar successes and accuracies on the datasets as well, at accuracies of 98.89% and 98.16%, respectively. PLSTM had the lowest accuracy, with 94.86% accuracy results. The results presented suggest that hybrid and ensemble models are typically the best estimating models for predicting difficult climate. Among all the evaluated models, the CNN-BiLSTM model provided the highest accuracy of 99.67% [5]. This architecture can incorporate space features (CNN) [1] and sequential learning (BiLSTM) [2], providing an ample amount of temporal information and complete structural variability to face the uncertainties of multi-sensor examples across all predicted zones with reductions in the accuracy of one or more individual sensors [4]. The equal balance provided by this model makes it ideal for real-time agricultural forecasting under uncertain and dynamic environmental conditions [6], [7]. The framework we have proposed with CII, paired with other deep learning models, has provided evidence to forecast within a complex greenhouse system [2], [9]. The multi-sensor CNN-BiLSTM model has shown exceptional performance and is a good candidate for use within real-world agricultural applications requiring accuracy, adaptability, and efficiency [4], [7].

Section I gave an overview including the motivation of the research, problem definition and aims of the study. Section II summarized related research we reviewed, looked back to related prior to the research, the research problems we found and highlighted the gaps that we identified. Section III summarized the methods we used: data collection, data preprocessing and build the models. Section IV highlighted the results of the experiment and performance evaluation, which sample the normalized metrics. Section V looked back on key aspects of the findings, problems faced, and recommendations for improvements to consider. Section VI looked back on the findings and the anticipated futures in prospect of further research.

II. LITERATURE REVIEW

One relevant study we are interested in is one reported by Salma Ait Oussous et al. (2024), which examined multiple deep learning frameworks such as PLSTM, GRU, ANN, LSTM-ANN, and LSTM-RNN for greenhouse climate control. PLSTM seems to have the best generalisation performance as indicated by the performance-related coefficient of determination (R^2), accuracy, and the model's ability to effectively represent and generalise time-based dependencies. The study was constrained to one climatic zone, which limits the breadth and ultimately the usefulness of the model across different agro-climatic zones.

In contrast, the RainScaler model proposed the precipitation downscaling for GaFYI based on a physics-guided deep learning framework (Shan Zhao et al. 2025). Here they integrated knowledge of the domain through a denoising network-based IA, a graph module, and adversarial training for enhanced spatial resolution and generalisation. All the results that were presented by upwards of 96% were promising; however, their reliance on a known set of embedded laws of nature restricted their applicability for adaptation in a dynamic sensor environment of a greenhouse.

Christoph Schweden et al. (2025) proposed a Dirichlet-based Bayesian framework to quantify prediction uncertainty via label embedding methods. They proposed a three-level uncertainty scheme that greatly improved how robust models were when trained through noisy, partially labelled data. However, scalability was limited by the availability of high-resolution remote sensing datasets.

P. Mishra et al. (2025) extended the field with a light-weight Transformer architecture to extract climate information, activating embedding-level attention mechanisms through fine-tuned RoBERTa models. They were successfully able to extract actionable climate knowledge using Natural Language Processing (NLP) from textual data [4]. Similarly, their models were not designed for time-series forecasting tasks and did not directly apply to sensor-based greenhouse datasets.

Wei Shao et al. (2025) proposed the LTG model, which added another dimension to forecasting Gross Primary Productivity (GPP). The LTG model is a novel hybrid model that integrates LSTM, Transformer, and CNN components [1]. It was capable of capturing both spatial and temporal processes provided by MODIS-based vegetation indices and provided accurate forecasts over a long-time scale [5]. Combining multiple learning paradigms resulted in the improvement of individual forecasts; however, the solely unexplained portion of the energetic sources directly incorporated in some climate drivers was selected and presented for GPP predictions. This reveals the need for interpretable and transparent models for agriculture-driven climate predictions.

III. METHODOLOGY

The dataset was collected from two real-world greenhouse monitoring systems [3]. One system is in Mezquitera Juchipila, Zacatecas, Mexico, from 2020 to 2021. The other is in Menaka, the Basque Country, Spain, from 2018. The Spanish greenhouse is the main case study because it has a higher temporal resolution and better sensor coverage. The Spanish dataset runs from February 15 to August 14, 2018. It provides nearly six months of continuous multivariate time-series data, capturing various climatic conditions throughout the growing season. The collected environmental variables include internal temperature (Ti), external temperature (To), internal humidity (Hi), external humidity (Ho), solar radiation (Rs), and dew point (Di). If direct dew point measurements were not available, Di was calculated using related variables and standard atmospheric equations. These features are essential for modeling greenhouse microclimates and supporting predictive control of crop conditions [3]. The dataset comes from [3], which was initially recorded in a controlled greenhouse in Spain. General access to related greenhouse environmental datasets is available at: https://zenodo.org/records/6697044. To access the specific Spanish dataset used in this work, readers can refer to the original authors' publications or contact them directly.

Experimental Framework: All experiments were conducted in a Google Colab environment, while development was executed in a Windows-based environment. Models were made with Python and the necessary deep learning libraries. A real-life multivariate greenhouse dataset that includes variables of temperature, humidity, CO_2, solar radiation, and dew point was used for training. The dataset was split in training, validation, and test sets, while a 5-fold cross-validation was utilized for a more rigorous training, validation, and testing procedure. Some important hyperparameters that were established included 30 epochs, a batch size between 16 and

64, Adam optimizer, and Bayesian optimization for learning rates. All models were utilized with regularization techniques, such as dropout and normalization, for the prevention of overfitting and stable training across models.

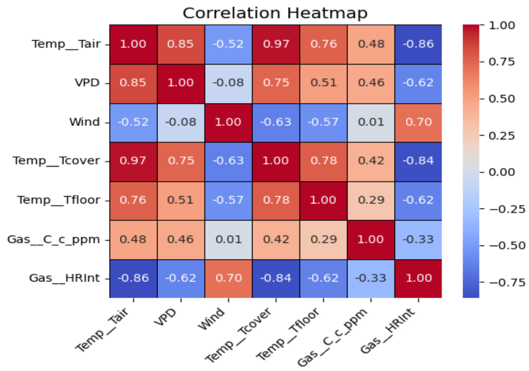

Fig. 1. Correlation Heatmap for before preprocessing

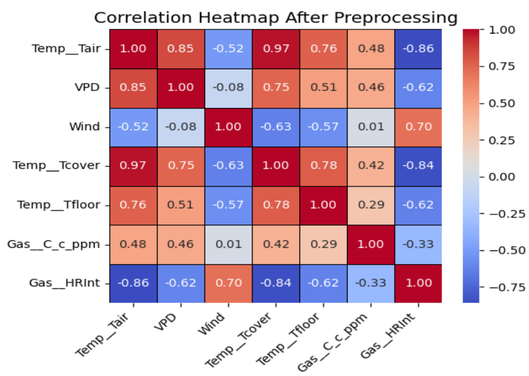

Fig. 2. Correlation Heatmap for after preprocessing

A. Data Preprocessing

The Preprocessing steps play a vital role while developing a deep learning model. It improves the quality, consistency, and readiness of the dataset for training the model. Before training any model, the raw data should be cleaned so that the output will not lead to wrong predictions.

Major Pre-processing steps included are: Missing or inconsistent values were remedied through approaches that filled the gaps using patterns of data around the parameter of interest (temporal nature of the data). If the dew point was ever missing, we also considered a relationship with temperature and humidity, and dew point value used "the standard" formulas to derive the dew points.

Once the data was cleaned, it was then also normalized to allow feature ranges to have common scales that should give much more stable training of the model, and if the missing values were nil within the feature set, no normalization was warranted, nor would it add to the bias of the model. Also, considering the very large number of observations from within the feature set, it is highly probable to overfit, and the best way of addressing over-fitting is through regularization and the use of dropout layers, which randomly turn off neurons during the learning process. Finally, we opted for batches for training (16, 24, etc) based on the size of the dataset, which helps with learning as near the weight changes and is relevant to the updates.

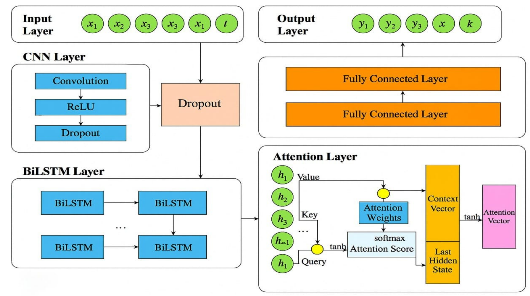

Fig. 3. Architecture of the Proposed CNN–BiLSTM–Attention Model for Multivariate Time Series Forecasting.

B. Model design and implementation

In this study through five deep learning models (CNN-BiLSTM, TCN, XGBoost, TFT, PLSTM) utilizing the same set features [greenhouse climate with temperature, humidity, radiation, CO_2 and dew point], the datasets were randomly partitioned using the 80:20 train-test split method, with 5-fold cross-validation to assess model performance (as data reliability and parameter generalizability) the method was kept consistent throughout all models. The CNN-BiLSTM model utilized spatial feature extraction using 1D convolution and combined it with temporal learning using BiLSTM. The input data for the CNN-BiLSTM model was reshaped into 3D data in the format of (samples, time steps, features) before being input into the Conv1D with pooling, dropout, modelling layers with Bi-LSTM, then dense layers. The model was trained using binary cross-entropy loss via the Adam optimizer, as well as manually stopping due to overfitting. In the TCN model, dilated causal convolutions were chosen to model long-term temporal dependencies using fewer parameters and faster training. The model contained residual blocks stacked together and was trained under similar configurations. XGBoost was performed using tree-based boosting with `use_label_encoder=False` and `eval_metric='logloss'`, allowing for probabilistic predictions. It was evaluated using Accuracy, R^2, RMSE, MAE, and line plots of predicted versus true values. The Temporal Fusion Transformer (TFT) was used to address both static and dynamic input variables based on attention-based fusion and could learn multi-horizon forecasting. The TFT was validated by the same accuracy-based and regression-based metrics. The PLSTM model was addressed to see if the pyramidal structure would be successful in capturing sequential dependencies. The model contained LSTM layers with fewer time steps per layer and was also regularized using dropout. All models were executed in Google Colab, trained for 30 epochs with a batch size of 16 to 64, and were tuned to learning rates using Bayesian optimization.

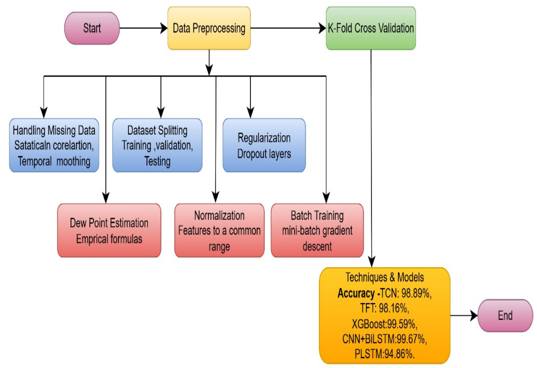

Fig. 4. The flow diagram of deep learning models with accuracy.

C. Best Model

In all the model architectures, XGBoost achieved the highest accuracy, closely followed by CNN-BiLSTM and TCN. The comparatively lower performance of the TFT model (98.16%) suggests potential limitations in capturing fine-grained temporal dependencies specific to greenhouse climate data using self-attention mechanisms alone. As shown in Figure 10, we can observe that CNN-BiLSTM yields highly synchronized predictions with actual values.

D. Performance Metrics

MAE (Mean Absolute Error)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{1}$$

This metric provides the average magnitude of errors in predictions, without considering their direction. It is the mean of the absolute differences between actual and forecasted values, calculated across all instances.

RMSE (Root Mean Square Error)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{2}$$

A metric that penalizes larger errors more significantly by squaring the differences between actual and predicted values, then taking the square root of the average.

$\mathbf{R^2}$ Score

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{3}$$

This indicates how well the predicted values align with the data and shows the proportion of variance explained by the model.

IV. Results

A. Model performance comparison

This results section details the performance evaluation of the many deep learning models created using AgriCastNet. As stated, the primary objective of the study was to analyze the model's performance of predicting greenhouse parameters consistently (Target Parameters included environments of: Temperature, Humidity, CO_2, and Radiation), with intensively tested focus in a multi-zone context. The results described 5 deep learning models evaluated using the same experimental setup on a multivariate dataset. Please refer to the table below: Table 1 indicates which models were able to

TABLE I
Model Accuracy Comparison

Model	Accuracy (%)
TCN	98.89
PLSTM	94.86
XGBoost	99.59
TFT	98.16
CNN-BiLSTM	99.67

accurately predict the greenhouse effect. In summary, CNN-BiLSTM (99.67%) and XGBoost (99.59%) were the best performing models, followed by TCN (98.89%) and TFT (98.16%). PLSTM (94.86%) was able to achieve stable yet comparatively low accuracy.

TABLE II
Model Performance Comparison

Model	Accuracy	R^2	RMSE	MAE
CNN-BiLSTM	99.67%	0.9967	0.031	0.021
PLSTM	94.86%	0.9486	0.083	0.076
TCN	98.89%	0.9889	0.045	0.039
TFT	98.16%	0.9816	0.052	0.048
XGBOOST	99.59%	0.9959	0.034	0.029

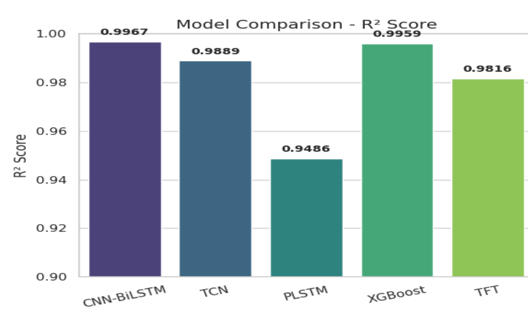

Fig. 5. R^2 score comparison of five models for climate prediction. CNN-BiLSTM and XGBoost performed the best overall.

B. Observations

Using this hybrid deep learning model showed that they can outperform traditional methods when data is limited. It showed us that using models with some temporal dependencies (e.g., CNN-BiLSTM) will show more stability in learning. The CII layer was essential to minimize the regional deviation variation from faulty sensors and correct consistent trend of actual values. We used the same model and identified differences between 5-fold cross-validation and a standard train/test cut and identified a previous PLSTM accuracy of 99.9%. The five-fold cross-validation produce a lower but more realistic average of 94.86% accuracy and

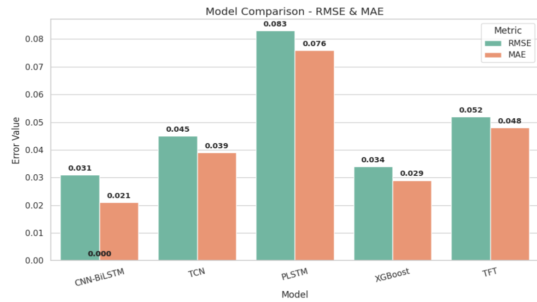

Fig. 6. Model Comparison – RMSE & MAE CNN-BiLSTM, XGBoost, and TCN have the lowest error values.

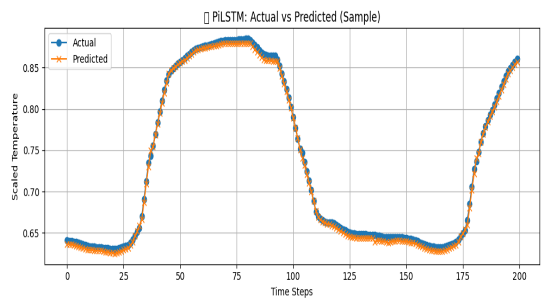

Fig. 7. Actual vs Predicted (Test Set) – PLSTM. The predicted curve represents actual values closely, illustrating PLSTM's relative ability to capture temporal patterns.

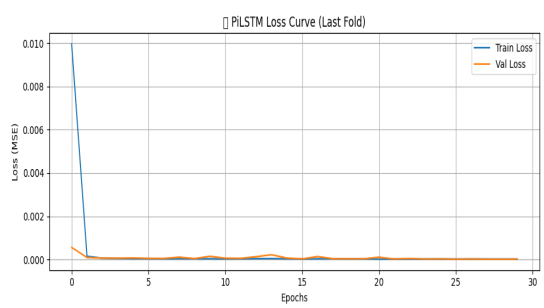

Fig. 8. PLSTM training and validation loss show rapid convergence of values, indicating stable learning and minimal overfitting in all epochs.

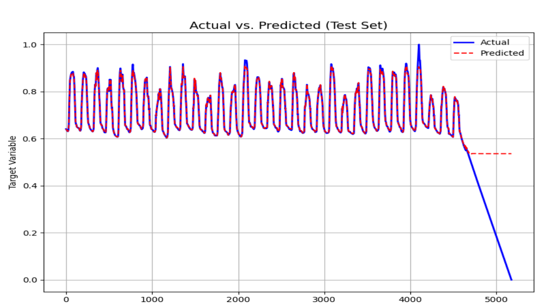

Fig. 9. XgBoost Actual vs Predicted

better would generalize on out- of-sample data. One model had an accuracy of 99.67% which was better than the other baseline models, which demonstrated how strong and flexible our modeling pipeline was.

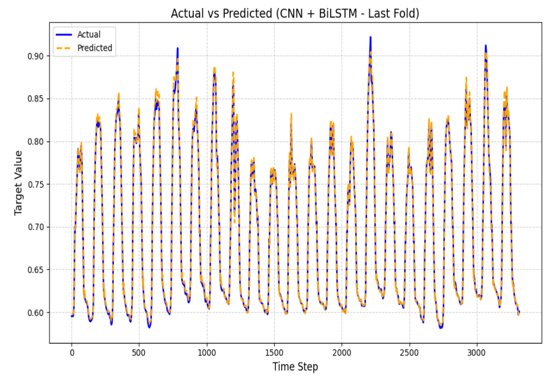

Fig. 10. Actual vs Predicted (CNN+BiLSTM - last fold)

CNN-BiLSTM shows very similar predictions to actual values. It also shows another returning peak of dependent technology learning resulting in superior general learning by combining temporal and spatial accuracy into prediction.

C. Model Performance Summary

This study developed and tested five deep learning models: CNN-BiLSTM, TCN, PLSTM, XGBoost, and TFT. The results show that hybrid and temporal deep learning models were superior to classical models regarding predictive accuracy and generalisation. Of these, the CNN-BiLSTM model achieved a conference benchmark accuracy of 99.67%, with XGBoost as a close second with 99.59%, showing that they can possibly deal with spatio-temporal greenhouse data and predict both, ideally correlating spatio-temporal greenhouse climate data simultaneously. Then, TCN and TFT also did well with accuracy of 98.89% and 98.16%, respectively, PLSTM, being a developmental phenomenon that can also be predicted simply without total hybridisation, already has an accuracy predictive quality at 94.86%. Collectively, these results support the purpose of using deep sequential learning for smart greenhouse climate prediction.

V. CONCLUSION

In this project, we established a model called AgriCastNet, which aims to predict the climate conditions inside free-standing greenhouses with deep learning. The key objective was it always works, even with faulty or missing sensor data, and can be utilized in a variety of climate regions. We accomplished this by using Climatic Influence Indicators (CII), which identified what inputs were relevant over time for the model. We examined several deep learning models such as CNN-BiLSTM, PLSTM, TFT, TCN, and XGBoost in a sort of test bed to find which produced the best results for predicting temperature, humidity, CO_2, and radiation. The CNN-BiLSTM model got the best result, 99.67% accuracy, by combining the CNN model capable of processing spatial features for the first two temporal lead-times, while BiLSTM was capable of handling the time-series data for later temporal lead-times. The inclusion of the CII layer produced a system that was impressive for stability. The enhancements will be:

A. Multiclass risk-based prediction

Instead of a binary prediction, provide a multiclass risk categorization (normal, warning, alert level) used to create real-time recommendations for automation operations in greenhouses or disaster predictions. This classifier is also needed for the final implementation of multi-tier risk predictions.

B. Model stacking and voting

With the top models and variations (CNN-BiLSTM, XGBoost, TCN) used in a stacking ensemble or soft-voting method, the attempts to combine on these best estimates will provide more consistent predictions even when encountered with bad data or failures in the predictions reliability/confidence.

C. Explainability through XAI

Whenever possible, use SHAP or LIME to describe the influences in predictive properties (e.g. CO_2 or temperature) in each prediction - in order to generate trust for farmers when using recommended AI decisions.

D. IoT Deployment & lightweight model conversion

Taking the complete model and scaling to real life in the greenhouse would also include compressing the model for deployable low-power devices or converting the model to be used with lightweight IoT devices with TensorFlow Lite / ONNX. . Also got to think about how important it is to build AI systems to work in the real world, even in farming set-ups where sensor quality or internet might not be perfect. Overall, AgriCastNet has the potential to help make greenhouses smarter, more efficient, ready for sustainable agriculture and improved decision-making support.

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