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Predictive Crop Growth Modeling Using Transformer-Enhanced Imputation of Agricultural Sensor Data

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Abstract: Smart farmland is getting better with the help of smart sensor networks that collect real-time data about the environment, like CO2 levels, temperature, and humidity. These continuous data streams allow predictive analytics to help crops grow better, but sensor readings that aren't full often make models less accurate, so they need effective ways to fill in missing data and make predictions. A Spark object is used to handle big amounts of data and make distributed computation easier for the Smart Farming Data 2024 (SF24) dataset, which is made up of multivariate time-series measurements from agricultural sensors. Conventional Long Short-Term Memory (LSTM) models often have trouble with missing or corrupted data, which makes it hard to predict crop growth accurately. To get around these problems, the FICformer method combines fuzzy Bayesian imputation with an encoder–decoder architecture based on transformers. The imputation part fills in missing sensor data using Bayesian calculations and fuzzy estimates to make sure the data is full and accurate. A dimensional temporal attention method is used to find correlations and dependencies between variables over time, and a pooling layer cuts down on duplicate data and computation time. To improve efficiency, hybrid and stacked configurations were made by putting together FICformer with GRU and Bidirectional GRU layers. The Stacked Former configuration got an RMSE of 2.746549%, which shows that it was very good at making predictions and did better than baseline LSTM, FICformer, and hybrid methods for smart agriculture systems.

***"Index Terms:** Agricultural Big Data, cross-attention transformer, decision support system (DSS), deep neuro-fuzzy technology, interpretable missing imputation."*

1. INTRODUCTION

The fast growth of digital technologies has changed modern farming by making it easier to handle resources and production processes more accurately and efficiently. Decision support systems (DSSs) have become very important in this situation because they turn complicated farming data into useful information that can be used right away [1]. DSSs help with timely actions that can increase yield, lower resource waste, and improve sustainability [2]. They do this by using knowledge about the environment, climate, and crops. Adding Big Data analytics to farming DSSs has made it easier to model how many factors interact with each other in complex ways. This makes it possible to make more accurate predictions about the environment and make better decisions ahead of time [3]. These skills are becoming more and more important as the world faces problems like changing climates, pest attacks, and a greater need for food security.

Even with these improvements, it will be hard to use DSSs effectively in agriculture because the environment is always changing and data collection isn't always full. A lot of the time, agricultural datasets have items that are missing or noisy, which can make predictive models and decision outputs less accurate and reliable [4]. Many traditional methods depend on having all the data they need, which makes them less reliable and useful in the real world [5]. Also, current prediction methods have a hard time capturing the complicated, nonlinear, and changing connections between different environmental and crop factors [6]. So, we really need methods that can deal with uncertainty, fill in the blanks when information is missing, and give us solid information in farming settings with many factors [7].

The study's goal is to fix these problems by creating a full framework for predictive modeling in smart agriculture that takes into account both missing data and unknowns in the environment. The main goal of the study is to make agricultural DSSs easier to understand and more reliable so that they can give good advice in a variety of situations. The framework aims to improve the quality of decisions while making the best use of existing agricultural data [8] by combining advanced prediction strategies with uncertainty modeling. The goals include making predictions that are more accurate, making sure that all the data is available, and letting people make smart decisions about a wide range of environmental and crop-related issues [9]. The method is meant to be scalable and flexible so that it can be used with a lot of different agricultural datasets and uses.

The importance of this work lies in its potential to make current farming methods more reliable, efficient, and long-lasting. The suggested framework can give stakeholders the power to make proactive, data-driven decisions that make the best use of resources, lower risks, and boost crop production [10]. It does this by dealing with both missing data and uncertainty. The method also lays the groundwork for more study into smart agriculture, especially when it comes to combining advanced decision support systems with multifactor environmental analysis. In the end, this work helps reach the bigger goal of making agriculture a stronger, smarter, and more sustainable industry.

2. LITERATURE REVIEW

Recent improvements in environmental and agricultural systems that are driven by data have made it clear how important it is to use correct data imputation and predictive modeling. Adhikari et al. [11] did a thorough review on how to fill in missing data in Internet of Things (IoT) apps, focusing on a number of statistical and machine learning-based methods. Their work showed how important it is to have strong methods that can deal with different and incomplete datasets, but these methods are still not very useful for studying complex natural systems. Chen et al. [12] suggested a Laplacian convolutional representation for traffic time series imputation that showed better stability over time and lower prediction error. However, the method is mostly used for structured traffic data and might not work well in multifactor farming settings. Peis and Hernández-Lobato [13] created deep hierarchical models that work with Hamiltonian Monte Carlo to fill in missing data, which allows for probabilistic uncertainty estimates. Even though this method is sound in theory, it can be hard to use on big agricultural datasets because it requires a lot of computing power.

In the field of environmental forecasting, Li et al. [14] created an encoder-decoder model with residual learning to predict soil wetness, which was much more accurate than previous methods. He et al. [15] also showed that gated recurrent unit (GRU) models are better at predicting low greenhouse temperatures using local weather data than other machine learning methods. This shows how important temporal modeling is. Liu et al. [16] looked into long short-term memory (LSTM) networks for predicting greenhouse gas emissions and proved that they are good at recording how things change over time. Even though these studies make big steps forward in predicting the environment, they often rely on full datasets, which makes them less reliable when data is missing or only partially observed, which is common in farming systems.

A number of studies have looked at multifactor agricultural uses and how to represent features. Kong et al. [17] suggested a multi-stream hybrid design with cross-level fusion to recognize fine-grained crop species. This would improve the accuracy of classification and the use of features. Wen et al. [18] used Big Data-driven time series prediction networks to make predictions about the sea environment. This showed how useful multivariable predictive models can be for complex ecological data. Wang et al. [19] created deep fuzzy cognitive maps for predicting multivariate time series in a way that can be understood. These maps combine uncertainty modeling with good prediction performance. These studies improve how features are shown and how they can be understood, but they ignore the problem of missing data and interactions between multiple factors, which can have a big effect on the accuracy of decision support in smart agriculture.

Even with these improvements, current methods still have major problems when it comes to dealing with incomplete datasets, simulating relationships between multiple factors, and figuring out how much uncertainty there is in real-life agricultural settings [20]. Most methods either focus on predicting the future or extracting features, but they don't fully incorporate uncertainty modeling and filling in missing data into a cohesive framework for prediction. This study aims to fill in that gap by creating a complete method that can deal with missing data, identify multifactor relationships, and make farming decision support systems easier to understand and more reliable. By filling in these gaps, the suggested work aims to make predictions more accurate and give strong, data-driven insights for smart farming uses.

3. MATERIALS AND METHODS

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Using real-time data from smart agricultural sensors, the suggested system aims to improve the ability to predict crop growth. The Smart Farming Data 2024 (SF24) dataset includes readings for temperature, humidity, and CO_2 levels, among other things. It is loaded and processed using a Spark-based distributed system that works well with large amounts of data. To fix sensor values that are missing or incomplete, a fuzzy Bayesian imputation module is used. This module combines matrix factorization and time-varying vector auto-regression. It uses fuzzy inference and Bayesian estimates to rebuild data while keeping it easy to understand. The FICformer algorithm is used for forecasting. It combines a transformer-based encoder–decoder model with a dimensional temporal attention mechanism and a pooling layer to find correlations between variables and over time while cutting down on unnecessary information. Also, hybrid and stacked setups that use both GRU and Bidirectional GRU layers improve feature extraction, sequential learning, and the stability of convergence. This method makes sure that crop growth predictions are correct, strong, and take into account the situation. It also helps smart, data-driven farm management make good decisions.

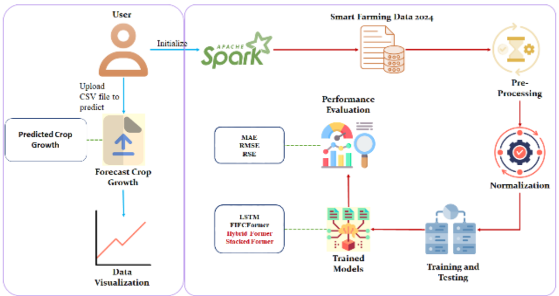
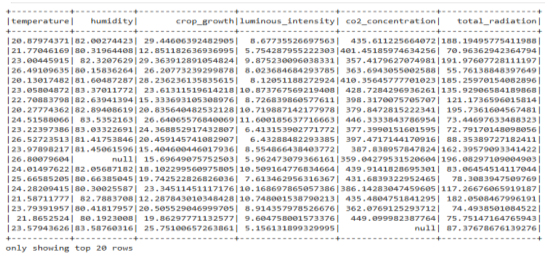


Fig.1 Proposed Architecture

Collecting environmental data, preprocessing it, and making predictions are all built into the system design to help farmers make smart decisions. It collects information about many aspects of agriculture in a planned way, such as climate, soil, and crop conditions. It then uses data imputation to fill in empty values. Advanced predictive modules in the design take into account the temporal and dimensional relationships between factors, which allows for accurate forecasting and decision support. Also, the uncertainty modeling and feature extraction parts make the results easier to understand and more reliable. This means that you can get useful, data-driven ideas for improving crop management and resource use.

a) Dataset Collection:

The Smart Farming Data 2024 (SF24) dataset, which is open to the public, will be used in the proposed study. This dataset has about 50,000 samples that were gathered by smart field sensors that were put to use in real-time farming settings. There are many environmental factors in each record, like temperature, humidity, CO2 levels, soil moisture, and light intensity. There are also goal labels that show how the crop is growing. The data set shows continuity over time, showing how the environment changed over the course of different cultivation stages. It has lost and inconsistent records because of sensor problems and transmission delays, but this makes it perfect for testing imputation and forecasting algorithms. SF24 is a freely available agricultural dataset that gives a more complete and high-resolution picture of smart farming conditions. This makes it possible to test how well predictive models work and how accurate decision-support models are in data-driven agriculture.



temperature	humidity	crop_growth	luminous_intensity	co2_concentration	total_radiation
20.87974371	82.00274423	29.44606392482905	8.67735526697563	435.611225664072	188.19495775411988
21.77046169	80.31964408	12.851182636936995	5.754287955222303	401.45185974634256	70.96362942364794
23.00445915	82.3207629	29.363912891054824	9.875230096038331	357.4179627074981	191.97607728111197
26.49109635	80.15836264	26.20773239299878	8.023684684293785	363.6943055002588	55.76138848397649
20.13017482	81.60487287	28.236236135835615	8.12051188272924	410.35645777701023	185.25970154082896
23.05804872	83.37011772	23.61311519614218	10.873767569219408	428.7284296936261	135.92906584189868
22.70883798	82.63941394	15.333693105308976	8.726839860577611	398.3170075705707	121.1736596015814
20.27774362	82.89408619	20.835640482532128	10.719887142177978	379.8472815222341	195.7361604567481
24.51588066	83.5352163	26.64065576840069	11.600185637716663	446.3333843786954	73.44697633488323
23.22397386	83.03322691	24.368852917432807	6.413153902771772	377.3990151601595	72.79170148098056
26.52723513	81.41753846	20.459145741082907	6.43288482293385	397.4717144170916	88.35389727182411
23.97898217	81.45061596	15.404600446017936	8.554866438403772	387.838957847824	162.39579093341422
26.80079604	null	15.69649075752503	5.962473079366161	359.04279531520604	196.08297109004903
24.01497622	82.05687182	18.102299560975805	10.509164776834664	439.9141828695301	83.06454514117044
25.66585205	80.66385045	19.742522826826036	7.613462956316367	431.6839322952465	78.3083947509769
24.28209415	80.30025587	23.34511451117176	10.168697865057386	386.14283047459605	117.26676065919187
21.58711777	82.7883708	12.287843010348428	10.748001538790213	435.4804751841295	182.0508467996191
23.79391957	80.41817957	20.505529046999705	8.914357978526676	362.0769125293712	74.4938501084522
21.8652524	80.1923008	19.86297771132577	9.604758001573376	449.099982387764	75.75147164765943
23.57943626	83.58760316	25.75100657263861	5.156131899329995	null	87.37678676139276

only showing top 20 rows

Fig.2 Dataset Collection

b) Pre-Processing:

Preprocessing is an important part of smart agriculture data analysis because it makes sure that the data is correct, full, and consistent. This improves the accuracy of predictions, the stability of models, and the dependability of decision-support systems that come after.

Data Cleaning: In this step, items in the collected sensor data that are missing, inconsistent, or not relevant are found and either deleted or fixed to make sure the dataset is complete. This process fixes mistakes that happen because of broken sensors, slow transmissions, or noise in the surroundings. Cleaning the data is important to improve the quality and reliability of future models, lower bias, and stop mistakes from spreading in predictive analyses. Smart farm systems need a clean dataset in order to make accurate predictions and help people make good decisions.

Missing Data Imputation: Fuzzy Bayesian imputation and other advanced methods that take into account temporal and multivariate relationships are used to reconstruct incomplete records. This process makes sure that the dataset is full, that the statistical properties and correlations are kept, and that sparsity doesn't hurt the performance of the model. Imputation improves the accuracy, interpretability, and robustness of agricultural decision-support forecasts by making sure that all inputs are fully informative.

Normalization: Normalization changes the sizes of all the input features to be in the same range. This makes it less important for feature sizes to be different when training a model. This step is very important in places with many sensors that record things like temperature, humidity, and CO_2 levels that use different units and scales. Normalization correctly makes sure that each feature adds equally to the learning process, speeds up convergence during training, and stops larger variables from dominating, all of which improve model stability and forecasting accuracy.

c) Training and Testing:

To get a good picture of how well the prediction works, the dataset is split into training and testing groups. About 80% of the data is used to train models, which helps algorithms figure out the patterns and connections between environmental factors. The last 20% is set aside for testing, which gives a neutral look at how accurate forecasting is on data that hasn't been seen yet. To figure out how big prediction errors are, performance measures like RMSE, MAE, and RSE are used. This methodical approach makes sure that the model can be used in a wide range of real-world farming situations and is reliable and strong.

d) Algorithms:

Existing LSTM: The Long Short-Term Memory (LSTM) model is used to find temporal relationships in sensor data from farming systems. Based on readings of the environment from the past, it learns sequential trends that help it predict crop growth. It can model time-series data, but it has trouble with datasets that aren't full or are noisy, which makes it less accurate. LSTM is used as a starting point to compare more complex algorithms. It makes initial predictions and shows how standard recurrent neural networks fail when dealing with missing data and complicated multivariate dependencies.

$$h_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \cdot \tanh(C_t) \qquad (1)$$

Proposed FICFormer: Fuzzy Bayesian imputation and a transformer-based encoder–decoder architecture are used together in FICFormer to improve crop growth forecasts. The fuzzy Bayesian module fills in missing or inconsistent sensor data, and the dimensional temporal attention system finds connections between variables and between time periods. A pooling layer cuts down on duplicate data and computer work, which lets you make more accurate guesses. This model makes it easier to understand, more reliable, and more scalable. It also does a much better job than regular LSTM at handling big, multidimensional agricultural datasets.

Hybrid Former: The Hybrid Former combines ICFormer with a GRU layer to improve feature extraction and learning from time sequences. This mix finds deeper dependencies in multivariate time-series farming data, which makes forecasting more stable and accurate. By using the best features of both transformer attention and recurrent architectures, it improves accuracy, cuts down on errors, and allows for adaptive modeling to adapt to changing environmental conditions. This makes crop growth forecasts more reliable even when sensor inputs change.

Stacked Former: To get the best forecasting results, the Stacked Former architecture blends FICFormer with Bidirectional GRU and GRU layers. It takes into account complicated links between variables and over time, allowing for very accurate and low-error predictions of crop growth. Multi-layer learning is used in the stacked arrangement to improve feature extraction, convergence, and robustness. When compared to other methods, this model is more accurate, giving trustworthy data-based information to help farmers make smart decisions.

4. EXPERIMENTAL RESULTS

RMSE: Root mean square error (RMSE) is a way to find the average difference between what a statistical model said would happen and what actually happened. It is the standard deviation of the residuals in math terms. The residuals show how far away the regression line is from the data points.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} ||y(i) - \hat{y}(i)||^2}{N}} \qquad (2)$$

MAE: Absolute Error is the amount of mistake when you measure something. It's the difference between what was recorded and what was "true." To

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give you an example, if the scale says you weigh 90 pounds but you know you really weigh 89 pounds, the scale is off by 1 pound.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

RSE: A simple predictor, like the mean of the true values, is used to compare the total squared error of a forecast model to the RSE.

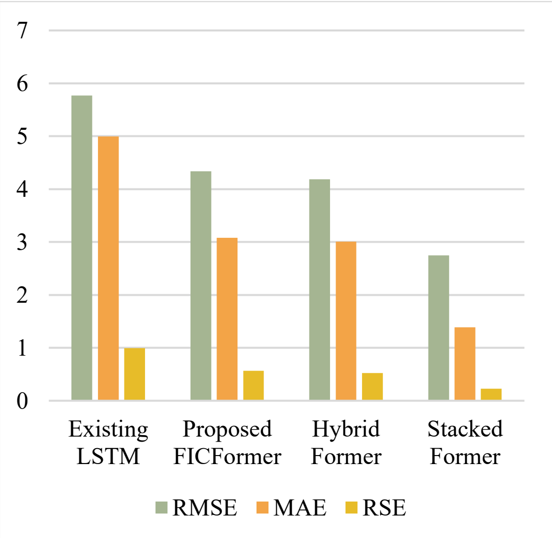
$$RSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (4)$$

Table.1 Performance Evaluation Table

Algorithm Name	RMSE	MAE	RSE
Existing LSTM	5.770100	4.997517	0.998103
Proposed FICFormer	4.338638	3.081271	0.564307
Hybrid Former	4.185052	3.007409	0.525062
Stacked Former	2.746549	1.390214	0.226143

RMSE, MAE, and RSE are used in Table (1) to compare the results of models. The Stacked Former has the lowest mistake rates and is more accurate at predicting than the LSTM, FICFormer, and Hybrid Former.

Fig.3 Comparison Graph



The comparison graph in Fig.3 shows the RMSE, MAE, and RSE values for each model. It is clear that the Stacked Former does better than the LSTM, FICFormer, and Hybrid Former by making the most accurate predictions.

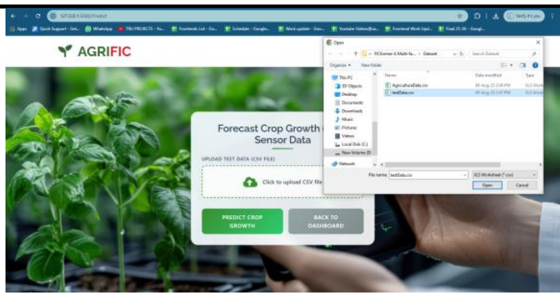


Fig.4 Upload a CSV File

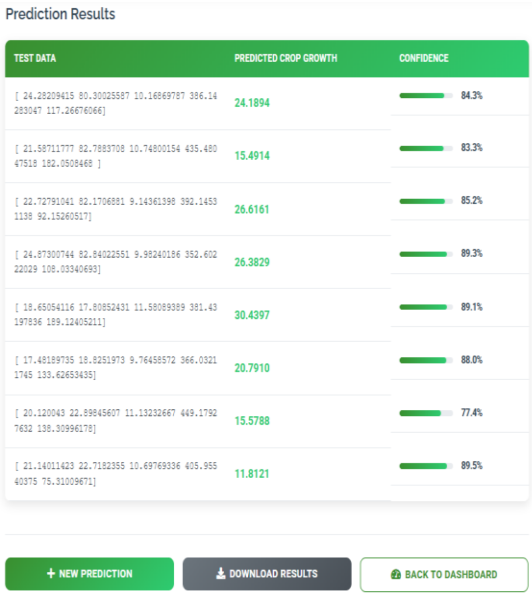


Fig.5 Predicted Result

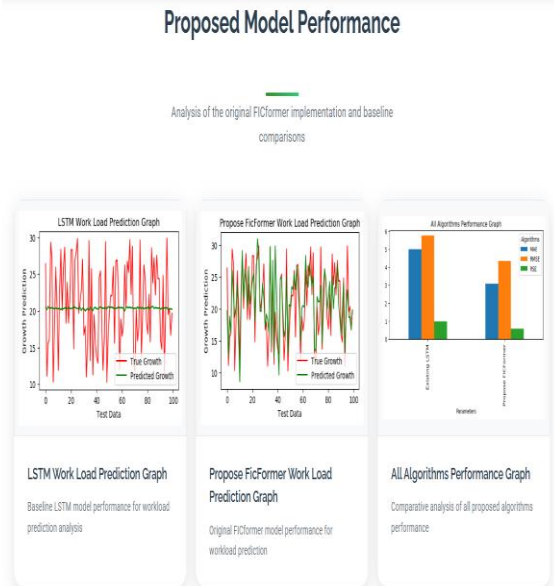


Fig.6 Proposed Model Performance

Fig.7 Extension Model Performance

5. CONCLUSION

Lastly, combining advanced machine learning frameworks with smart agricultural sensing creates an environment that is very flexible for planning how to handle crops in the future. Using a Spark object to process the Smart Farming Data 2024 (SF24) dataset makes it easier to handle big amounts of data and do distributed computations for training and testing models. Traditional LSTM-based forecasting had a lot of problems because sensor records weren't full and time wasn't well represented. To fix these problems, the suggested FICformer algorithm uses fuzzy Bayesian imputation with a transformer-driven encoder–decoder framework to fill in missing data and make the model easier to understand. The fuzzy Bayesian part uses probabilistic reasoning and fuzzy inference to correctly find missing sensor readings. The dimensional temporal attention system, on the other hand, sees how variables and time depend on each other. Adding a pooling system cuts down on duplicate work and computer time without affecting accuracy. Furthermore, hybrid and stacked designs with GRU and Bidirectional GRU layers showed significant progress. The RMSE for the Stacked Former configuration was 2.746549 percent, which shows that it is reliable and accurate for smart farm forecasting.

This system can get better at predicting and analyzing the future by incorporating more multimodal data sources, like satellite images, tracking drones, and sensors that measure soil nutrients. Using models for explainable artificial intelligence (XAI) can make decision-making even more clear and trustworthy for users. In the future, improvements could include real-time deployment using edge computing for research on the field and adaptive learning models that can change as the seasons and weather do. Adding blockchain technology could also make sure that everyone sharing data does so safely. This would create an open, data-driven environment for precision agriculture and long-term food management.

REFERENCES

[1] Tahir, H. A., Alayed, W., & Hassan, W. U. (2025). A Federated Explainable AI Framework for Smart Agriculture: Enhancing Transparency, Efficiency, and Sustainability. IEEE Access.

[2] Rezk, N. G., Attia, A. F., El-Rashidy, M. A., El-Sayed, A., & Hemdan, E. E. D. (2025). An efficient IoT-based crop damage prediction framework in smart agricultural systems. Scientific Reports, 15(1), 27742.

[3] Kumar, S., & Kumar, M. (2024, September). Enhancing agricultural decision-making through an explainable AI-based crop recommendation system. In 2024 International Conference on Signal Processing and Advance Research in Computing (SPARC) (Vol. 1, pp. 1-6). IEEE.

[4] Shams, M. Y., Gamel, S. A., & Talaat, F. M. (2024). Enhancing crop recommendation systems with explainable artificial intelligence: a study on agricultural decision-making. Neural Computing and Applications, 36(11), 5695-5714.

[5] Dr, K, Pushpa Latha., Mr, M, N, Mallikarjuna Reddy., Dr, B, Rajalingam., Malleswari Akurati., Dr, G, Swapna., Bakkala Santha Kumar., (2026). Blockchain-Enabled Trade Finance Framework for Secure Drug Supply Chain Transactions., International Journal of Drug Delivery Technology, 16(3s), 884-889.

[6] B. Fang, C. Zheng, H. Wang, and T. Yu, “Two-stream fused fuzzy deep neural network for multiagent learning,” IEEE Trans. Fuzzy Syst., vol. 31, no. 2, pp. 511–520, Feb. 2023.

[7] G. Onoufriou, M. Hanheide, and G. Leontidis, “Premonition Net, a multi-timeline transformer network architecture towards strawberry tabletop yield forecasting,” Comput. Electron. Agriculture, vol. 208, 2023, Art. no. 107784.

[8] Gudditti, V., & Krishna, P. V. (2021). Adaptive Light Weight Encryption Algorithm for Securing Multi-Cloud Storage. Turkish Journal of Computer

and Mathematics Education (TURCOMAT), 12(9), 545–554.

[9] J. Kong et al., “BMAE-Net: A data-driven weather prediction network for smart agriculture,” Agronomy, vol. 13, 2023, Art. no. 625.

[10] Q. Tu, Q. Zhang, Z. Zhang, D. Gong, and M. Tang, “A deep spatiotemporal fuzzy neural network for subway passenger flow prediction with COVID-19 search engine data,” IEEE Trans. Fuzzy Syst., vol. 31, no. 2, pp. 394–406, Feb. 2023.

[11] D. Adhikari et al., “A comprehensive survey on imputation of missing data in Internet of Things,” ACM Comput. Surv., vol. 55, Dec. 2022, Art. no. 38.

[12] Kumar, C. S., Sirisati, R. S., Gudditti, V., Rao, K. S., & Challa, R. K. (2022, December). A smart recommendation system for medicine using intelligent NLP techniques. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 1081-1084). IEEE. https://doi.org/10.1109/ICACRS55517.2022.10029078

[13] C. M. Peis and J. M. Hernández-Lobato, “Missing data imputation and acquisition with deep hierarchical models and Hamiltonian monte carlo,” in Proc. Adv. Neural Info. Syst., 2022, vol. 35, pp. 35839–35851.

[14] Q. Li et al., “Improving soil moisture prediction using a novel encoder-decoder model with residual learning,” Comput. Electron. Agriculture, vol. 195, 2022, Art. no. 106816.

[15] Z. He et al., “Gated recurrent unit models outperform other Machine learning models in prediction of minimum temperature in greenhouse Based on local weather data,” Comput. Electron. Agriculture, vol. 202, 2022, Art. no. 107416.

[16] Y. Liu et al., “A long short-term memory-based model for greenhouse climate prediction,” Int. J. Intell. Syst., vol. 37, pp. 135–151, 2022.

[17] J. Kong, H. Wang, X. Wang, X. Jin, X. Fang, and S. Lin, “Multi-stream hybrid architecture based on cross-level fusion strategy for fine-grained crop species recognition in precision agriculture,” Comput. Electron. Agriculture, vol. 185, Aug. 2021, Art. no. 106134.

[18] J. Y. Wen, B. Jiang, H. Song, and H. Wang, “Big Data driven marine environment information forecasting: A time series prediction network,” IEEE Trans. Fuzzy Syst., vol. 29, no. 1, pp. 4–18, Jan. 2021.

[19] J. Wang, Z. Peng, X. Wang, C. Li, and J. Wu, “Deep fuzzy cognitive maps for interpretable multivariate time series prediction,” IEEE Trans. Fuzzy Syst., vol. 29, no. 9, pp. 2647–2660, Sep. 2021.

[20] Korapati, Dolasankar., Viswanath, G., G, Prathyusha., (2023) A Real-Time Video Based Vehicle Classification, Detection And Counting System, Industrial Engineering Journal,52(9), 474-480.

[21] H. Wu, J. Xu, J. Wang, and M. Long, “Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting,” in Proc. Adv. Neural Inf. Process. Syst., 2021, vol. 34, pp. 22419–22430.

[22] W. Lin and C. Tsai, “Missing value imputation: A review and analysis of the literature (2006–2017),” Artif. Intell. Rev., vol. 53, no. 2, pp. 1487–1509, 2020.

[23] K. Akpoti, A. Kabo-bah, and S. Zwart, “Agricultural land suitability analysis: State-of-the-art and outlooks for integration of climate change analysis,” Agriculture Syst., vol. 173, pp. 172–208, 2019.

[24] F. Gutierrez, N. Htun, F. Schlenz, A. Kasimati, and K. Verbert, “A review of visualisations in agricultural decision support systems: An HCI perspective,” Comput. Electron. Agriculture, vol. 163, Aug. 2019, Art. no. 104844.

[25] X. Chen, Z. He, Y. Chen, Y. Lu, and J. Wang, “Missing traffic data imputation and pattern discovery with a Bayesian augmented tensor factorization model,” IEEE Transp. Res. C, Emerg. Technol., vol. 104, pp. 66–77, Jul. 2019.

[26] X. Pham and M. Stack, “How data analytics is transforming agriculture,” Bus. Horiz., vol. 61, no. 1, pp. 125–133, 2018.

[27] C. Faloutsos, J. Gasthaus, T. Januschowski, and Y. Wang, “Forecasting big time series: Old and new,” Proc. VLDB Endowment, vol. 11, no. 12, pp. 2102–2105, 2018.

[28] S. Yang and J. Liu, “Time-series forecasting based on high-order fuzzy cognitive maps and wavelet transform,” IEEE Trans. Fuzzy Syst., vol. 26, no. 6, pp. 3391–3402, Dec. 2018.

[29] A. Vaswani et al., “Attention is all you need,” Adv. Neural Inf. Process. Syst., vol. 30, pp. 5998–6008, 2017.

[30] S. Capalbo, J. Antle, and C. Seavert, "Next generation data systems and knowledge products to support agricultural producers and science-based policy decision making," Agric. Syst., vol. 155, pp. 191–199, 2017.