

FICformer: A Hybrid Fuzzy-Transformer Framework for Agricultural Data Imputation and Forecasting

¹Gopu Hasini, ¹Suram Venkata Raawi Teza, ¹Moturi Vijay Ramchandra, ²T.P.Shekhar

^{1*}Student, Department of Information Technology, Sreenidhi Institute of Science and Technology, Hyderabad, Telangana, India

^{2*}Asst. Professor, Department of Information Technology, Sreenidhi Institute of Science and Technology, Hyderabad, Telangana, India

Abstract— Smart agricultural developments are moving towards intelligent sensor networks that are now gathering real-time environmental information, including temperature, humidity, and CO₂ concentration. Even though partial sensor measurements can often decrease model performance, such real-time data streams enable predictive analytics to enhance crop development, and require effective data imputation and forecasting methods. A Spark object is employed to process the SF24 data to handle large volumes of data and perform remote computations, where the data are multivariate time-series readings of agricultural sensors. Irregular crop growth forecasting is caused by the fact that conventional LSTM algorithms are often unable to deal with anomalies in data. The FICformer technique combines a transformer-based encoder-decoder design with fuzzy Bayesian imputation to overcome these drawbacks. To provide data completeness and reliability, imputation component employs Bayesian-based fuzzy guesses to reconstruct missing sensor data. A pooling layer minimizes redundancy and computing time and a dimensional temporal attention approach is employed to obtain temporal dependencies and inter-variable correlations. GRU and BidirectionalGRU were applied to FICformer to design hybrid and layered designs that enhanced performance. The Stacked Former configuration had the highest predictive accuracy of smart agriculture systems with an RMSE of 2.746549, compared to baseline LSTM, FICformer, and hybrid approaches, with outstanding predictive accuracy.

Keywords— *Agricultural Big Data, cross-attention transformer, decision support system (DSS), deep neuro-fuzzy technology, interpretable missing imputation.*

I. INTRODUCTION

Modern agriculture has been completely changed by the quick development of digital technology, which allow for more accurate and effective resource and production process management. DSSs in this context have become important instruments that provide stakeholders with viable insights out of complex agricultural data [1]. DSSs allow real-time reactions to achieve the maximum possible production, reduce resource squandering and increase sustainability through the use of environmental, meteorological, and crop data [2]. Simulation of complex interactions among numerous parameters has also been boosted by the integration of the Big Data analytics in the agricultural DSSs which enables them to make more accurate environmental predictions and forecasts [3]. Such capacities are increasingly gaining significance in

the face of global challenges such as insect epidemic, climatic fluctuations and the increasing demand of food security.

In spite of this, not good data gathering and environmental uncertainties are a major challenge to effective DSSs application in agriculture. The predictive models and decision outputs can be compromised as the agricultural datasets often contain missing or noisy data [4]. Traditional techniques may be weakened by their reliance on the availability of comprehensive data in real life situations [5]. Moreover, the interactions of numerous environmental and agricultural factors are often complex, nonlinear and dynamic and are often hard to capture using current prediction methods [6]. Approaches that are capable of effectively handling uncertainty, consider missing data, and provide reliable information in multifactor farming scenarios are thus sorely required [7].

By creating a thorough framework for predictive modeling in smart agriculture that concurrently takes environmental uncertainties and partial data into account, this study seeks to overcome these constraints. The goal of the project is to improve agricultural DSSs' interpretability and resilience so they can offer trustworthy advice in a variety of scenarios. This strategy would make the best of current agricultural data and improve the quality of decision-making through the combination of complex prediction algorithms and uncertainty models [8]. These objectives are to enhance the accuracy of forecasting, improve the completeness of the data and enable informed decision making on numerous crop-related and environmental factors [9]. The approach is flexible and scalable, which is why it can be used with many types of agricultural data and applications.

It is significant as it may lead to more sustainable, reliable, and efficient modern agriculture. The proposed solution can help stakeholders make active, evidence-based decisions that can help maximize the utilization of resources, minimize risks, and enhance the productivity of agriculture [10]. This is because it deals with both ambiguity and missing data. Also, the method provides the background of future studies in smart farming, i.e., in the field of a multifactor environmental analysis along with advanced decision support systems. Finally, this effort supports the greater mission of turning agriculture into a smarter, more resilient and sustainable industry.

II. RELATED WORK

New developments in data-driven agricultural and environmental systems have put the importance of accurate data imputation and predictive modeling in the limelight. An extensive literature overview of missing data filling in IoT applications was given by Adhikari et al. [11], who highlighted many statistical and machine learning techniques. Although their applicability to complex environmental systems is limited, their work has shown that it is important to have powerful procedures that have the ability to work with a variety of incomplete datasets. Chen et al. [12] proposed a Laplacian convolutional variant of filling missing traffic time series data and demonstrated that it resulted in the data being more consistent across time and reduced prediction errors. The method however is primarily organized traffic data and may not be as effective in agricultural settings involving a lot of factors. Peis and Hernandez-Lobato [13] introduced deep hierarchical architecture coupled with the use of Hamilton Monte Carlo to do missing data imputation to estimate uncertainty probabilistically. This method is theoretically valid, but it may be very time-consuming to operate and not very applicable to large agricultural data.

Li et al. [14] created an encoder-decoder model with residual learning for predicting soil moisture in the field of environmental forecasting. This model was significantly more precise as compared to the ones of the past. He et al. [15] also demonstrated that GRU-based models are superior to other machine learning techniques in the prediction of the lowest greenhouse temperatures based on local meteorological data. This shows how important it is to simulate time. Liu et al. A further investigation into LSTM networks in the climate forecasting of greenhouse was conducted by [16] who found that they could be used to measure the temporal correlations. Though these studies are important developments in predicting the environment, they assume complete datasets, which limits their use in cases where complete data is not available such as in agricultural systems.

Many studies have been conducted on multifactorial agricultural applications and representation of features. Kong et al. [17] released a multi-stream hybrid scheme with cross-level fusion to identify fine-grained crop species, which enhanced classification with more precise and useful features. Wen et al. [18] applied Big Data-based time series prediction networks to predict marine environments, highlighting the effectiveness of multi-variable predictive models of complex ecological data. Wang et al. [19] introduced interpretable multivariate time series prediction based on deep fuzzy cognitive maps, and managed to combine uncertainty modeling and predictive efficacy. Although these studies enhance the representation and interpretability of the features, in most cases, they do not consider the joint problem of missing data and multifactor interaction, which may significantly undermine the reliability of decision support in smart agriculture.

Nevertheless, even with these developments, the existing methods still have a serious flaw in dealing with partial information, in terms of simulating multifactor interaction, and uncertainty measurement in real agricultural contexts

[20]. Most approaches either focus solely on feature extraction, or predictive time without fully integrating uncertainty modeling and missing data imputation into a unified predictive model. The purpose of this gap is the fuel to the present project that is to offer a comprehensive strategy capable of managing the lack of data, multifactor interaction, and enhance the explanativeness and reliability of agricultural decision support systems. The suggested initiative aims to seal the following gaps to enhance the accuracy of predictions and provide substantiated and evidence-based insights on intelligent use of agriculture.

III. MATERIALS AND METHODS

The proposed system aims at enhancing prediction of crop development using real-time environmental information collected by smart agricultural sensors. A Spark-based distributed architecture is adopted to ingest and analyze the SF24 dataset (time series observations with multi-dimensional time-series data i.e. temperature, humidity and CO2 levels) to effectively manage large-scale data. Missing or incomplete sensor readings are dealt with using a fuzzy Bayesian imputation module, which integrates matrix factorization and a time-varying vector auto-regression. This module is based on fuzzy inference and Bayesian estimation to reconstruct data without losing interpretability. Forecasting is done using the FICformer method that is a transformer-based encoder decoder model with a dimensional temporal attention mechanism and pooling layer to capture inter-variable and temporal dependencies and reduce duplication. Moreover, hybrid and stacked topologies, which use GRU and Bidirectional GRU layers, are better than sequential learning, feature extraction, and convergence stability. The method will provide accurate, reliable and context sensitive crop growth predictions, which will provide reliable decision support services to intelligent and fact-based farming management.

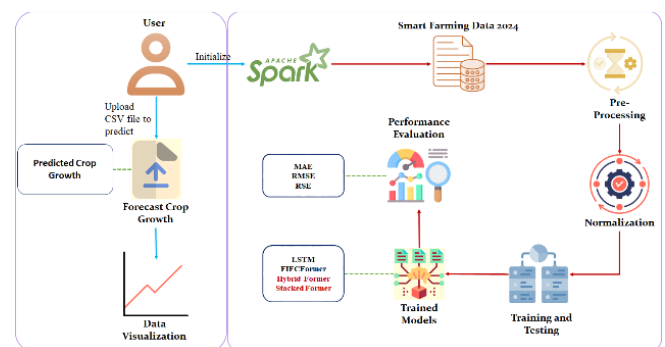


Fig. 1. System Architecture

The system design helps to support intelligent agricultural decision-making with the combination of environmental data collection, preprocessing and predictive modeling. It gathers multifactor agricultural information (e.g., crop conditions, soil, and climate) systematically and imputes the blanks with techniques of data imputation. The architecture has advanced predictive modules that enable it to make accurate forecasts and provide decision support by capturing time and dimensional associations among the data. Moreover, uncertainty model and feature extraction elements enhance

the interpretability and reliability, ensuring successful, data-driven information to maximize crop management and resource utilization.

A) Dataset Collection

The SF24 dataset, which is accessible to the public, is used in the proposed study. Smart agricultural sensors fitted in real farming environments were used to collect about 50,000 samples to this dataset. Besides goal labels as indicators of crop development, every record has a number of environment-related traits, such as temperature, humidity, CO₂ concentration, soil moisture, and light intensity. The data set reflects dynamic alterations in environmental conditions across multiple growing seasons indicating continuity over time. This characteristic renders it the best to evaluate imputation and prediction algorithms, even though it has inconsistent and missing values due to sensor failures, and delays in transmissions. In comparison to other publicly available agricultural datasets, SF24 provides a more comprehensive and detailed description of smart farming conditions, which can be assessed reliably to evaluate prediction performance and accuracy of the decision-support model 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	80.31964488	12.851182636936995	5.754287955222303	401.45185974634256	70.96362942364794
23.00445915	82.3207629	29.363912891854824	9.8752380996038331	357.4179627074981	191.97067728111197
26.49180635	80.15836264	26.20773239299878	8.023584684293785	363.6943055902580	55.76138048397549
20.13017482	81.60487287	28.236236135835615	8.120511882729204	410.356457777018023	185.25970154082896
23.05804872	83.37011772	23.61311519614218	10.873767569219408	428.7284296936261	135.92066584189868
22.70883798	82.63941394	15.333693105308976	8.726839860577611	398.3170075705707	121.1736596015814
20.2774362	82.89408619	20.835640482532128	10.719887142177978	379.8472815222341	195.7361604567481
24.51588066	83.5352163	26.64065576840069	11.600185637716663	446.3333843786954	73.44697633488323
23.22397386	83.0322691	24.368852917432807	6.413153902771772	377.3990151601595	72.79170148098056
26.52723513	81.41753846	20.459145741082907	6.43288482293385	397.4717144170916	88.35389727182411

Fig. 2. Dataset Collection

B) Pre-Processing

Preprocessing is an important process of intelligent agricultural data analysis to ensure that the data is accurate, comprehensive, and consistent. This enhances the reliability of the models, the anticipated accuracy and the reliability of future decision support systems.

Data Cleaning: This step determines, removes or corrects any absent, erroneous or redundant information in the sensor data gathered to maintain integrity of the data sets. The process corrects errors caused by malfunctions of sensors, transmission delay, or noise. Precautions Data cleaning is necessary to minimize bias, guard against errors propagating into predictive analysis and improve the quality and reliability of later modeling. Clean data is needed to enable smart agricultural systems to generate accurate forecasts and decision support.

Missing Data Imputation: Partial records are reconstructed by advanced techniques taking into account both time-related and multivariate relationships, e.g., fuzzy Bayesian imputation. This process keeps the data full, preserves its statistical properties and correlations and does not allow the sparsity to deteriorate the performance of the model. The imputation improves the predictive accuracy, interpretability and longevity of agricultural decision-support projections by making sure that the inputs are fully informative.

Normalization: Normalization reduces the impact of differences in the magnitude of features on the training of a model by scaling all input feature scales to a common range. This step is a necessity in the case of multi-sensors, where readings vary in scales and units such as temperature, humidity, and CO₂ levels. To enhance the stability of models and accuracy of predictions, appropriate normalization ensures that the individual features play the right role in the learning process, accelerates convergence during training, and prevents the higher aspects of individual variables to dominate.

C) Training and Testing:

The dataset is divided into training and testing subsets to adequately evaluate the performance of prediction. In order for algorithms to discover underlying patterns and interactions among environmental variables, about 80% of the data is utilized for model training. To obtain an objective assessment of predicting the performance on unobserved data, the rest 20% is reserved to be tested. The performance measures such as RMSE, MAE, and RSE are used to measure prediction error. This systematic approach ensures the strength, reliability and applicability of the model in real agricultural conditions.

D) Algorithms

Existing LSTM: The LSTM model is used to extract temporal correlations in sensor agricultural data. It forms a sequence of patterns in predicting crop growth based on historical environmental observations. Though it is able to model time-series data its accuracy is poor in cases where there is noisy or incomplete data. With the capability to provide initial forecasts and reveal the deficiencies of traditional recurrent neural networks in handling missing data and multivariate relationships, LSTM can be used as a baseline algorithm to compare more complex algorithms.

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

Proposed FICFormer: FICFormer enhances predictions of crop growth by integrating a transformer based encoder and decoder architecture with fuzzy Bayesian imputation. The dimensional temporal attention mechanism is used to store inter-variable and temporal correlations whereas the fuzzy Bayesian module is used to recover missing or incoherent sensor data. A pooling layer enables making more accurate predictions and reduces the complexity and redundancy of computing. Our model greatly outperforms traditional LSTM on the interpretability, reliability, and scalability of large-scale, multi-dimensional agricultural data.

Hybrid Former: The Hybrid Former is an ICFFormer with a GRU layer to enhance temporal sequence learning and feature extraction. This combination enhances forecasting accuracy and stability, by extracting richer relationships in the multivariate time-series agricultural data. It enhances predictive accuracy, reduces errors and enables adaptive modeling to dynamic environmental conditions using the free transformer attention and recurrent architectures, which

ensures more accurate crop growth forecasts in a variety of sensor inputs.

Stacked Former: The Stacked Former design that integrates FICFormer with Bidirectional GRU and GRU layers is used to maximize the forecasting performance. It offers very accurate and low-error crop growth predictions by modeling the complex interactions of time and inter-variables. The stacked architecture provides better features, convergence and robustness, through multi-layer learning. Our model is more precise than other approaches and provides reliable and data-driven information to support intelligent agricultural decision making.

IV. EXPERIMENTAL RESULTS

RMSE: The RMSE can be applied to establish how different are the predicted values of a statistical model and the actual values. In mathematics it is the standard deviation of the residues. The gap between the data points and the regression line is shown by the residuals.

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

MAE: The absolute error is the amount of error in your measurements. The difference between the real value and the measured value is called the discrepancy. The absolute error amount to 90 pounds minus 89 pounds or 1 pound, when there is a scale which indicates that you are 90 pounds when you know you are 89 pounds.

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

RSE: The RSE compares the total squared error of a prediction model against a simple predictor (the mean of true values).

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

Table. 1. Performance Evaluation

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

The Table (1) performance evaluation compares models using RMSE, MAE, and RSE metrics. The Stacked Former achieves the lowest error values, outperforming LSTM, FICFormer, and Hybrid Former in predictive accuracy.

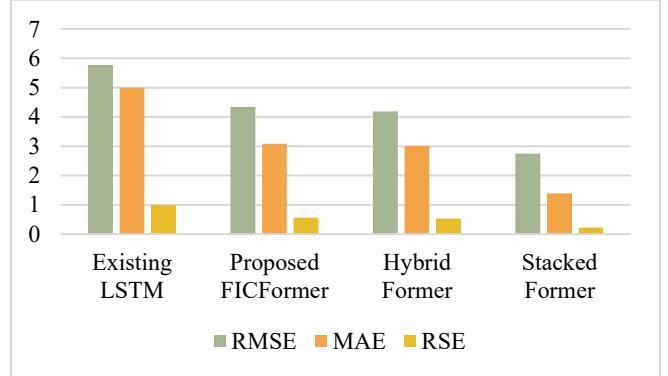


Fig. 3. Comparison Graph

The Stacked Former outperforms LSTM, FICFormer, and Hybrid Former because it had the lowest forecasting errors, which is evident by the comparison graph (Figure 3) that shows RMSE, MAE, and RSE values in each model.

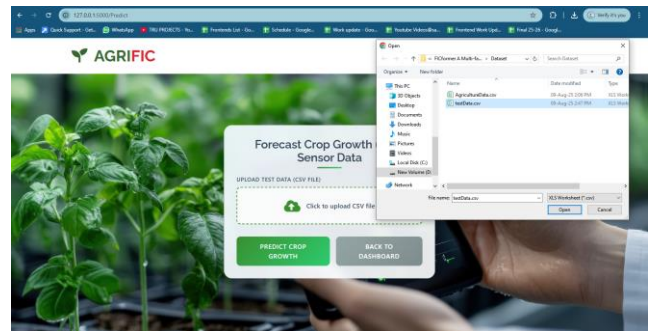


Fig.4 Upload a CSV File

When the user loads a CSV file with the test sensor data, the system produces the expected values of crop growth as seen in Fig. 4.

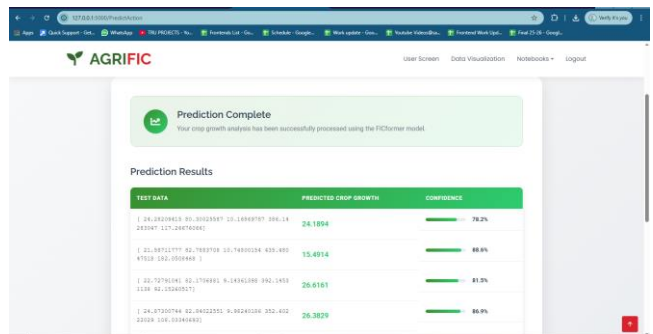


Fig.5 Predicted Result

Fig. 5 illustrates the expected crop growth by displaying the test results, projected values and associated confidence scores in a table.

V. CONCLUSION

Finally, an advanced machine learning framework along with smart agricultural sensing can be used to create a highly adaptable environment needed to predictively manage crops. By processing the SF24 dataset based on a Spark object, distributed computing and efficient handling of large-scale

data becomes achievable to test and train the models. Due to insufficient temporal representation and inadequate sensor recordings, traditional LSTM-based forecasting shown notable shortcomings. To deal with these issues, the proposed FICformer method is an encoder-decoder network based on a transformer and fuzzy Bayesian imputation to restore the missing data and enhance model interpretability. The fuzzy Bayesian element does the task of restoring missing sensor data correctly by probabilistic reasoning, fuzzy inference and the dimensional temporal attention mechanism records the correlations between the variables and time. A pooling technique ensures reduced processing costs and redundancy without compromising accuracy. Moreover, hybrid and stacked structures with GRU and Bidirectional GRU layers were found to be significantly enhanced. The Stacked Former architecture was more accurate and reliable at intelligent agricultural forecasting with the RMSE of 2.746549%.

The future of this system lies in its predictive and analytical capabilities, which can be improved by greater integration of multimodal data sources such as satellite images, drone-based monitoring and soil nutrient sensors. XAI frameworks can also help to enhance transparency and user confidence in the decision-making process. The future developments may also involve adaptive learning models which can adjust to seasonal and climatic variations and real-time deployment with edge computing to analyze on-field. Moreover, blockchain technology could ensure that the participants can exchange data safely, which would allow fostering a data-driven ecosystem, where participants collaborate to achieve sustainable crop management and precision farming.

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] Martin, R. J., Mittal, R., Malik, V., Jeribi, F., Siddiqui, S. T., Hossain, M. A., & Swapna, S. L. (2024). XAI-powered smart agriculture framework for enhancing food productivity and sustainability. *IEEE Access*.
- [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] Z. Qu et al., "Temperature forecasting of grain in storage: A multi-output and spatiotemporal approach based on deep learning," *Comput. Electron. Agriculture*, vol. 208, 2023, Art. no. 107785.
- [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] X. Chen, Z. Cheng, N. Saunier, and L. Sun, "Laplacian convolutional representation for traffic time series imputation," 2022, arXiv:2212.01529.
- [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] H. Zhou et al., "Informer: Beyond efficient transformer for long sequence time-series forecasting," in *Proc. 35th AAAI Conf. Artif. Intell.*, 2021, pp. 11106–11115.
- [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.



International Journal of DATA SCIENCE AND IOT MANAGEMENT SYSTEM

Peer Reviewed, Referred & Indexed Journal

ISSN: 3068-272X

www.ijdim.com

Original Research Paper

- [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.