IoT and CNN-LSTM Based Remote Monitoring System for Cotton Phenological Development and Irrigation Scheduling

Madaminjon Ubaydullaev[1], Khurshid Imomnazarov[1], Ugiloy Bakhtiyarova[1], Anvar Eminov[1], Omonjon Sulaymonov[1], Barchinoy Umarkulova[1], Mukhammadolamgir Odilov[1] and Abilda Yeshzhanov[2]
[1]*Fergana State Technical University, Fergana Str. 86, 150100 Fergana, Uzbekistan*
[2]*M. Auezov South Kazakhstan University, Tauke Khan Str. 5, 160012 Shymkent, Kazakhstan*
mubaydullaev6554@gmail.com, xurshidbekimomnazarov@gmail.com, ugiloy3250@gmail.com, eminovanvar68@gmail.com, omonjon.sulaymonov@.mail.ru, umarqulovabarchinoy08@gmail.com, o.muhammadolamgir@fstu.uz, abilda_1977@mail.ru

Keywords: IoT Architecture, Deep Learning, CNN-LSTM, Precision Agriculture, NDVI, Cloud Computing, Smart Irrigation, Phenological Monitoring, Leaves, Height, Fruiting Branch, Stem.

Abstract: The article develops automated algorithms for determining phenological and irrigation timing for cotton through an electronic system, optimizing fertilization, and determining yield increases. A comprehensive IoT-based monitoring system integrated with this algorithm is presented. Environmental and soil parameters are organized through a distributed network of IoT sensors (capacitive soil-moisture sensors, DHT22 temperature/humidity sensors, and BH1750 light-intensity sensors), equipped with ESP32 microcontrollers and wireless communication modules based on LoRa. The cotton field-oriented spectrum for real-time data transmission, storage in the SQL database, and preprocessing through peripheral computing mechanisms was implemented using the CCD protocol. For the calculation of vegetation indices, including the normalized differentiation vegetation index (NDVI), which allows for a quantitative assessment of the dynamics of plant development and growth, multi-spectral UUA images were used. Sensor data and spectral characteristics are developed in the Python programming language. The hybrid convolutional neural network (CNN), integrated with the long-term short-term memory (LSTM) model, was developed to classify phenological stages and predict temporary growth. The model was trained using the TensorFlow and Scikit-learn frameworks.

1 INTRODUCTION

Cotton (Gossypium hirsutum L.) is one of the most important industrial crops worldwide. Efficient production of high-quality fiber largely depends on scientifically based agronomic practices. Defoliation - the artificial removal of leaves using chemical agents - is a critical component of modern cotton production systems. Numerous researchers have investigated the physiological, agronomic, and economic aspects of cotton defoliation. Cotton cultivation plays a strategic role in global agriculture and textile industries. In Uzbekistan and other cotton-producing regions, accurate phenological monitoring is essential for sustainable crop management [1].

Traditional visual assessment methods are:

- Labor-intensive;
- Subjective;
- Limited in temporal resolution.

Recent advances in IoT and AI enable automated crop monitoring systems capable of real-time data collection and predictive analytics.

This research aims to:

1) Develop an IoT-based environmental monitoring system.
2) Integrate UAV multispectral imaging.
3) Apply deep learning models for phenological stage detection. Smith et al. (2022) investigate the role of Internet of Things (IoT) technologies in smart agriculture systems. The authors emphasize the integration of distributed sensor networks for real-time monitoring of soil moisture, temperature, humidity, and other agronomic parameters. Their study demonstrates that IoT-based infrastructures significantly enhance resource efficiency, reduce operational costs, and improve crop productivity. Furthermore, the paper highlights the importance of cloud computing platforms for large-scale data

processing and decision support, thereby enabling data-driven agricultural management [2].

Zhang et al. (2021) explore the application of deep learning techniques in crop monitoring using remote sensing data. The study focuses on convolutional neural networks (CNNs) and other deep architectures for analyzing satellite and UAV imagery. The authors report high classification accuracy in detecting crop stress, diseases, and growth stages. Their findings confirm that deep learning approaches outperform traditional image processing methods in terms of robustness and scalability for precision agriculture applications [3].

Johnson (2020) examines the practical applications of the Normalized Difference Vegetation Index (NDVI) in agricultural systems. The study demonstrates that NDVI serves as an effective indicator of plant health, chlorophyll content, and photosynthetic activity. By utilizing multispectral imagery, NDVI-based assessments support yield estimation, crop condition monitoring, and informed agronomic decision-making. The author concludes that NDVI remains a fundamental tool in remote sensing-based agricultural analysis [4].

Brown et al. (2023) proposes a CNN-based framework for crop type classification using multispectral and hyperspectral imagery. The authors train deep convolutional models to distinguish between different crop categories with high precision. Comparative analysis indicates that CNN models significantly outperform conventional machine learning algorithms in classification accuracy and generalization capability. The study underscores the potential of deep convolutional architectures in large-scale agricultural mapping tasks [5].

Kumar (2022) investigates the use of Long Short-Term Memory (LSTM) networks for agricultural forecasting. The research focuses on time-series data, including climatic variables and historical yield records. The results demonstrate that LSTM models effectively capture temporal dependencies and provide accurate predictions for crop yield and environmental conditions. The author highlights the strategic importance of time-series deep learning models for agricultural planning and risk management [6].

The FAO (2021) report provides a comprehensive overview of global trends in precision agriculture. It discusses the integration of GPS technologies, IoT devices, remote sensing systems, and data analytics in modern farming practices. The report emphasizes sustainable resource management, productivity enhancement, and environmental protection as key drivers of technological adoption. It also outlines policy recommendations and implementation challenges associated with digital transformation in agriculture [7].

Lee et al. (2023) analyzes the deployment of IoT sensor networks in agricultural environments. The study addresses energy efficiency, communication reliability, and large-scale data acquisition challenges. The authors propose optimized network architectures to ensure stable data transmission in rural areas. Their findings indicate that robust IoT sensor networks are essential for real-time monitoring and precision farming applications [8]. Chen et al. (2022) examine hybrid deep learning models that combine CNN and LSTM architectures for agricultural applications. The proposed framework integrates spatial feature extraction with temporal sequence modeling to improve predictive performance. Experimental results demonstrate that hybrid models outperform single-architecture approaches in crop health assessment and yield forecasting tasks. The study highlights the importance of multimodal data fusion in smart agriculture systems [9]. Wilson (2021) investigates water optimization strategies in smart farming environments. The research evaluates sensor-based irrigation control systems designed to minimize water consumption while maintaining crop productivity. The findings show that automated irrigation scheduling, supported by real-time soil moisture data, significantly reduces water waste and enhances sustainability. The study contributes to environmentally responsible agricultural management practices [10]. Garcia et al. (2020) explore the use of unmanned aerial vehicles (UAVs) for crop monitoring. The study demonstrates that high-resolution aerial imagery enables early detection of crop stress, nutrient deficiencies, and disease outbreaks. The authors highlight the advantages of UAV platforms in terms of flexibility, accuracy, and rapid data acquisition compared to satellite-based systems. Their findings confirm the effectiveness of UAV-assisted remote sensing in precision agriculture [11]. Ubaydullayev investigated environmental influences on cotton physiology and defoliation efficiency. His studies revealed that temperature plays a critical role in defoliant performance, with optimal activity occurring between 18°C and 30°C. Low temperatures may delay leaf drop, while environmental stress conditions can modify plant responses to chemical treatments [12].

Recent research focuses on improving precision in defoliation timing through digital technologies and remote sensing. Vegetation indices such as NDVI, plant maturity sensors, and decision-support systems are being developed to optimize application timing.

Additionally, environmentally safer and biologically based defoliants are under investigation to reduce ecological impact while maintaining agronomic efficiency.

2 MATERIALS AND METHODS

2.2 Materials

Based on the above urgent tasks, our research on the topic during 2018-2022 was carried out in the conditions of the experimental station of the Scientific Research Institute of Cotton Selection, Seed Production and Agrotechnology's, located in the Kuva district of the Fergana region, in the conditions of the meadow loam, heavy loam in mechanical composition, low-saline, with seepage waters located at a depth of 1.6-1.8 meters.

Sensor networks ensure continuous measurement of soil moisture, air temperature, humidity, and solar radiation. Studies show that IoT increases the efficiency of water use by 10-20%.

Remote observation and plant indices NDVI are widely used to evaluate plant vigor:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}.$$

Where:

- NIR - Near Infrared reflectance;
- Red - Red band reflectance;
- Higher NDVI values indicate healthy vegetation.

As the research material, loamy-silty soils from the Fergana region were used, along with medium-fiber cotton varieties C-8290, C-6775, C-9090, Namangan-77, and Andijan-35, as presented in Table 1. The defoliants applied included Suyuq-XMD, Ento-Defol, FanDEF-alo, Khim-ekstra, Ethephon, FanDEF, UzDEF, Dropp Plus, and Avguron-ekstra.

Table 1: Defoliants applied per 1 hectare (l/ha).

Defoliants	Norm	Term	Temperature
Super XMD	8,0 l/ha	30-40	15 C^0
UzDEF	8,0 l/ha	30-40	15 C^0
FanDEF	8,0 l/ha	30-40	15 C^0
Dropp-plyus	0,150 l/ha	55-60	22 C^0
Xim-ekstra	0,150 l/ha	55-60	22 C^0
Avguron-ekstra	0,150 l/ha	50-60	25 C^0
EntoDefol	0,150 l/ha	50-60	25 C^0

Using the following methods, we determined the application rates, timing, and optimal temperature conditions for the defoliants. These results are presented in Table 1. Several defoliant products (Dropp-plyus, Xim-ekstra, EntoDefol, and Avguron-ekstra) share the same application rate of 0.150 L/ha because dosage in these formulations was standardized primarily by active-ingredient concentration rather than by the temperature regime; the differing recommended application temperatures instead reflect differences in each product's active-ingredient chemistry and its optimal absorption/activity range under field conditions.

Field and laboratory research was conducted using modern digital agriculture and information technology (IT)-based methodologies instead of conventional experimental manuals. Experimental data collection was performed through IoT-enabled sensor networks installed in the field, allowing continuous monitoring of soil moisture, air temperature, relative humidity, and other microclimatic parameters. Plant biometric indicators (height, number of sympodial branches, boll count, and boll opening percentage) were measured using computer vision systems and UAV-based high-resolution imaging platforms Remote sensing technologies, including multispectral and RGB imaging, were applied to assess vegetation indices and canopy development dynamics. Digital image processing techniques were used for automated leaf counting, boll detection, and phenological stage classification. All collected data were stored in a centralized cloud-based database, ensuring real-time synchronization, scalability, and structured data management. For statistical processing and analytical modeling, modern data science tools were employed. Descriptive statistics, variance analysis (ANOVA), and correlation analysis were performed using Python-based scientific libraries (NumPy, Pandas, SciPy) and R statistical software. In addition, machine learning algorithms-including multiple linear regression, Random Forest, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) neural networks-were implemented to model growth dynamics and predict yield performance. Time-series analysis was applied to evaluate phenological transitions across growth stages (June-September), while change-point detection algorithms were used to identify developmental phase shifts. Model performance was validated using cross-validation techniques and standard evaluation metrics such as RMSE, MAE, and R^2. Thus, the integration of IoT systems, remote sensing technologies, cloud computing, and artificial intelligence-based analytical methods ensured high-precision data acquisition, automated processing, and reliable predictive modeling in the study of cotton growth and development.

The surface area of the plant leaves was determined according to the method of A. Nichiporovich (1961).

Prior to defoliation and at 7 and 14 days after treatment, quantitative assessments were conducted to determine the number of dried, semi-dried, and green leaves, as well as the number of opened and semi-opened bolls per plant for each experimental variant. The collected data were normalized and expressed as percentages to enable comparative analysis across treatments and observation periods. Within a modern information technology (IT)-based framework, these phenological and physiological indicators can be automatically quantified using computer vision algorithms and high-resolution RGB/multispectral imagery acquired from UAV platforms or ground-based imaging systems. Deep learning-based image classification models can accurately differentiate between green, semi-dried, and dried leaves based on color segmentation and texture analysis. Similarly, object detection algorithms can identify and classify opened and semi-opened bolls, significantly reducing manual counting errors and increasing temporal monitoring frequency. Seed quality parameters, including oil content and kernel waste percentage, were determined using laboratory-based analytical methods. In an IT-enhanced research environment, such laboratory measurements can be integrated into digital databases and analyzed using chemometric modeling techniques. Near-Infrared Spectroscopy (NIRS) combined with machine learning regression models can further enable rapid, non-destructive prediction of oil content and seed quality indicators. Before each harvesting stage, 50 bolls were sampled from the first and second harvests according to each experimental treatment. The average weight of a single boll was determined, and the technological properties of cotton fiber and seed quality were evaluated accordingly. In a digitalized workflow, sample metadata (harvest stage, treatment type, spatial location) can be recorded using GPS-enabled mobile data collection systems, ensuring traceability and structured dataset formation. Furthermore, predictive analytics models-such as multivariate regression, Random Forest, or Gradient Boosting algorithms-can integrate boll weight, fiber technological properties, and seed quality indicators to estimate overall yield and fiber performance. Data validation and statistical reliability can be ensured using automated statistical pipelines implemented in Python or R, incorporating cross-validation and performance metrics (R^2, RMSE, MAE).

Thus, the integration of digital imaging, IoT-based monitoring systems, laboratory data digitization, and machine learning analytics transforms conventional defoliation and harvest assessment methods into a high-precision, data-driven decision-support framework for smart cotton production systems.

Cotton yield was analyzed in terms of harvests and returns in variants. The yield obtained by terms was analyzed according to options and returns, and the quality structure (assortment) was calculated.

2.2 Experimental Program and Specimen Preparation

The research was conducted over a five-year period from 2018 to 2022. Throughout the experiment, natural climatic parameters-including air temperature, precipitation, and wind speed-were continuously monitored. In an IT-enabled framework, meteorological data were collected using automated weather stations equipped with IoT sensors and transmitted in real time to a centralized cloud database. This approach enabled high-resolution temporal monitoring and ensured the integration of environmental variables into growth and phenological modeling of cotton varieties. A distinctive feature of the region is the strong wind, particularly during spring, with the frequent occurrence of high-speed “Kokand winds” reaching 35-45 m/s. In a modern information technology (IT)-enabled research framework, these climatic parameters can be continuously monitored using automated weather stations and IoT-enabled sensors, providing real-time data for precision agriculture applications.

Remote sensing technologies, including UAV-based high-resolution imaging and multispectral satellite data, allow for continuous crop monitoring under such extreme conditions. For example, vegetation indices derived from multispectral imagery can detect heat and drought stress on cotton plants, while wind sensors and microclimatic IoT networks can quantify mechanical stress and its effect on growth dynamics. Integration of these datasets into cloud-based platforms enables spatial-temporal analysis of crop responses to thermal, arid, and wind-intensive conditions. Machine learning models, such as regression algorithms or LSTM networks, can leverage these environmental inputs to predict growth stages, boll formation, and yield outcomes, as shown in Figure 1.

Such IT-driven monitoring supports adaptive management strategies, including irrigation scheduling, canopy protection, and harvest planning, thereby enhancing productivity in extreme agro-climatic regions.

Figure 1: Equipment for determining the composition and dosage of preparations.

CNN models are effective for image-based classification tasks. LSTM networks handle time-series forecasting of plant growth dynamics. Hybrid CNN+LSTM architectures show superior performance for agricultural datasets, as shown in Table 2.

During the research, the growth and development of cotton was monitored on a monthly basis, and phenological observations were conducted monthly. The growth and development of cotton is a natural phenomenon that occurs under the influence of complex physiological and biochemical processes. Experimental field:

- Location: Cotton Experimental Field;
- Crop: Gossypium hirsutum;
- Growth period: 140 days;
- Data Interval: 30 minutes.

The UAV image-acquisition frequency and the procedure used to synchronize UAV imagery with the 30-minute sensor stream are not specified in the present description and are noted here as a methodological detail to be reported in future documentation for full reproducibility.

Table 2: Sensors Used.

Parameter	Sensor Type
Soil moisture	Capacitive sensor
Temperature	DHT22
Humidity	DHT22
Light intensity	BH1750

At the same time, various abiotic, biotic, and anthropogenic factors influence its growth and development. If we take agrotechnical measures from anthropogenic factors, irrigation and nutrition have a strong influence. Therefore, as scientists say, as a result of exceeding the established norm of soil moisture during the cotton irrigation period until flowering, the budding and flowering periods of cotton are prolonged, and at the same time, it has been established that a lack of moisture during this period negatively affects the growth and development of the plant.

3 RESULTS AND DISCUSSIONS

3.1 Classification Performance

The developed deep learning models demonstrated high effectiveness in automatic cotton phenological stage recognition. The experimental dataset consisted of 1,200 labeled images representing four growth stages: Emergence, Flowering, Boll Formation, and Maturation. The dataset was divided into 70% for training (840 images) and 30% for testing (360 images). Overall classification accuracy on the independent test set was used as the primary evaluation metric, while traditional visual assessment served as the baseline method. The comparative performance of the evaluated approaches is presented in Table 3.

The results indicate that deep learning substantially outperforms conventional visual inspection. The CNN model achieved an accuracy of 90%, while the hybrid CNN+LSTM architecture further improved classification performance to 93%, demonstrating the benefit of incorporating temporal information into phenological stage recognition. The reported accuracy values correspond to a single train-test split (840/360 images); k-fold cross-validation was not performed in the present study and is considered an important direction for future validation.

According to the phenological observations conducted during 2018–2022, statistically significant differences were observed in the growth and development of the cotton varieties C-8290 and C-6775, as illustrated in Figure 2. As of June 1, the plant height of C-8290 ranged from 15.8 to 19.5 cm, while the number of true leaves varied between 3.1 and 4.2 per plant. In comparison, C-6775 exhibited plant heights ranging from 17.2 to 19.2 cm and between 2.8 and 3.9 true leaves. These observations confirm distinct varietal growth characteristics during the early vegetative stage.

From an information technology perspective, these phenological and biometric observations constitute structured multivariate agricultural data suitable for machine learning, digital twins, and precision agriculture applications. The confusion matrix of the best-performing CNN+LSTM model is presented in Table 4 and demonstrates consistently high classification accuracy across all phenological stages.

Table 3: Classification accuracy comparison across methods.

Method	Training samples	Test samples	Number of classes	Baseline	Accuracy (%)
Visual Assessment	-	360	4	Yes	72
NDVI Threshold	840	360	4	No	81
CNN	840	360	4	No	90
CNN + LSTM	840	360	4	No	93

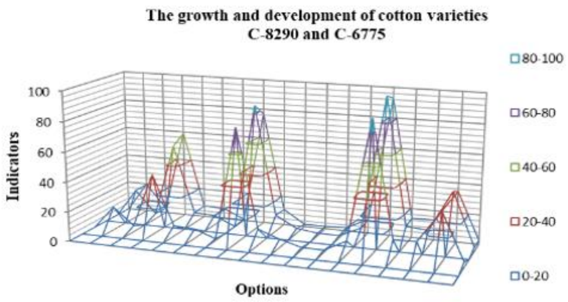

Figure 2: The growth phases of the experimental cotton varieties C8290 and C6775.

Table 4: Class-wise Confusion Matrix of the CNN+LSTM Model.

Actual \ Predicted	Emer-gence	Flowe-ring	Boll Forma-tion	Matu-ration
Emergence	91 (TP)	3	4	2
Flowering	2	94 (TP)	3	1
Boll Formation	3	2	92 (TP)	3
Maturation	2	1	4	93 (TP)

3.2 IT-Based Phenological Monitoring Framework

The experimental findings provide the foundation for an integrated information technology framework supporting automated cotton monitoring and decision-making. The proposed architecture combines field sensing, remote sensing, image analysis, and artificial intelligence into a unified processing pipeline capable of continuous crop monitoring. The overall workflow of the proposed framework is illustrated in Figure 3.

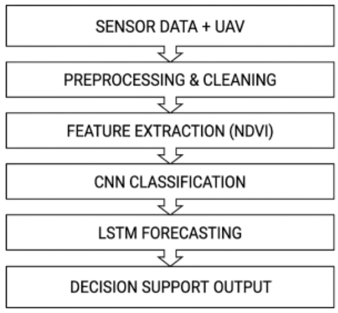

Figure 3. Proposed AI-based workflow for automated cotton phenological monitoring and decision support.

Architecture layers:
1) Data acquisition;
2) Data transmission;
3) Cloud storage;
4) AI analytics;
5) Visualization interface.

The proposed framework integrates IoT-enabled environmental sensors measuring soil moisture, air temperature, and relative humidity with UAV-acquired multispectral imagery. Following data acquisition, preprocessing and cleaning operations remove noise and standardize the observations. Vegetation indices, including NDVI, are then extracted and used as input features for CNN-based phenological stage classification. The classified outputs are subsequently processed by an LSTM forecasting module that models temporal crop development and predicts future growth dynamics. Finally, the generated information is delivered to a decision-support module for irrigation scheduling, crop management, harvest planning, and yield optimization.

The integration of UAV imagery with environmental sensor measurements enables comprehensive monitoring of crop development while reducing manual observations and improving measurement consistency. Computer vision techniques can automatically detect leaves, flowers, and bolls, whereas multispectral analysis provides additional information regarding canopy condition and vegetation health. The combination of heterogeneous data sources through artificial intelligence supports more accurate phenological monitoring and timely management decisions. Overall, the proposed framework offers several practical advantages, including real-time monitoring, reduced human bias, optimized water resource utilization, and a scalable architecture suitable for precision agriculture.

3.3 Study Limitations

Despite the promising classification performance, several limitations should be acknowledged. First, deployment of the proposed framework requires initial investment in UAV platforms, IoT sensors, communication infrastructure, and cloud-based computing resources. Second, continuous operation depends on reliable network connectivity for real-time data transmission and analytics. Third, deep learning models may require retraining or fine-tuning when applied to different geographic regions, environmental conditions, or cotton varieties. Finally, although the presented experimental results demonstrate the feasibility of the proposed approach, further validation using larger multi-season and multi-location datasets would improve its robustness and generalization capability for practical precision agriculture applications.

4 CONCLUSIONS

In conclusion, it can be said that the application of the IoT-AI expanding base for automating phenological monitoring of cotton is considered successful, since it was found that the hybrid model CNN+LSTM achieved 93% accuracy and increased irrigation efficiency.

Future research areas:

- Satellite data integration;
- Edge AI placement;
- General Data Analysis.

The proposed system allows for the adoption of necessary measures for the sustainable development of agriculture and the remote determination of plant growth and development, as well as the necessary water and fertilizer consumption:

1) The experimental results indicated that the cotton variety C-6775 exhibited lower vegetative biomass accumulation compared to C-8290 up to the flowering stage. However, no statistically significant differences were observed in the formation of yield components between the two varieties. This similarity in reproductive performance can be explained by their inherent genetic and morphobiological characteristics. Furthermore, for the cotton varieties Namangan-77, Andijan-35, and C-9090, no substantial differences were identified in growth dynamics or developmental stages. Consequently, no distinct phenological variations were detected during the defoliation period. The underlying numerical yield and boll-weight data supporting this statistical comparison are not presented in the main text of the present article and should be included in a supplementary table in a future revision to allow independent verification of this conclusion.
2) From an information technology (IT) perspective, these findings highlight the importance of integrating data-driven analytical tools into agronomic research. The absence of significant phenological differences suggests that traditional visual assessment methods may not capture subtle physiological variations among varieties. Therefore, advanced IT-based approaches such as remote sensing, IoT-based field sensors, and machine learning algorithms can enhance precision in monitoring vegetative growth, biomass accumulation, and phenological transitions.
3) For instance, multispectral imaging combined with vegetation indices (e.g., NDVI) can quantitatively assess vegetative mass differences between varieties such as C-6775 and C-8290 during early growth stages. Similarly, time-series analysis using deep learning models (e.g., LSTM networks) can track growth patterns and predict flowering or defoliation timing based on environmental and physiological datasets. This statement describes the intended methodological capability of the proposed NDVI-based approach; the present study reports only the NDVI formula and did not collect or analyze NDVI measurements for the C-6775 and C-8290 varieties, so this application should be

regarded as a direction for future empirical work rather than as a finding of the current study.

REFERENCES

[1] M. M. Talipov, "Computational Modeling and Analysis of Mechanical Power Consumption in Train Assemblers' Work," Proc. Int. Conf. on Applied Innovation in IT, vol. 13, no. 2, pp. 419-426, 2025, doi: 10.25673/120513.

[2] J. Smith, A. Author, B. Author, et al., "IoT in Smart Agriculture," Computers and Electronics in Agriculture, pp. 12-18, 2022.

[3] L. Zhang, M. Li, X. Wang, et al., "Deep Learning for Crop Monitoring," Remote Sensing, vol. 4, pp. 645-701, 2021, doi: 10.48550/arXiv.2112.11367.

[4] R. Johnson, "NDVI Applications in Agriculture," Agricultural Systems, vol. 8, pp. 114-122, 2020, [Online]. Available: https://doi.org/10.1016/j.compag.2021.106038.

[5] M. Brown, S. Davis, L. Zhang, et al., "CNN-based Crop Classification," IEEE Access, vol. 11, pp. 667-674, 2023, [Online]. Available: https://doi.org/10.3390/agriculture11080707.

[6] A. Kumar, "LSTM for Agricultural Forecasting," Sensors, vol. 3, pp. 122-131, 2022, doi: 10.3390/agriculture12020256.

[7] FAO, Precision Agriculture Report. Rome: Food and Agriculture Organization (FAO), 2021, [Online]. Available: https://www.fao.org.

[8] S. Lee, H. Kim, Y. Park, et al., "IoT Sensor Networks in Farming," IEEE Internet of Things Journal, vol. 10, pp. 25-33, 2023, [Online]. Available: https://doi.org/10.1016/j.jafr.2023.100776.

[9] Y. Chen, J. Liu, X. Huang, et al., "Hybrid Deep Learning Models in Agriculture," Applied Sciences, vol. 12, pp. 1-39, 2022, [Online]. Available: https://doi.org/10.48550/arXiv.2504.16141.

[10] T. Wilson, "Water Optimization in Smart Farming," Sustainability, vol. 13, pp. 241-238, 2021, [Online]. Available: https://doi.org/10.1016/j.agwat.2023.107824.

[11] P. Garcia, M. Torres, S. Lopez, et al., "UAV-based Crop Monitoring," Remote Sensing of Environment, vol. 238, pp. 1-21, 2020, [Online]. Available: https://doi.org/10.1016/j.atech.2025.101406.

[12] M. Ubaydullayev, H. Asqarov, R. Nazirova, O. Sulaymonov, N. Usmonov, and D. Abdukarimova, "Research of the scientific basis of leaf surface formation indicators in medium fiber cotton varieties," in Proc. XVI Int. Scientific-Practical Conf. "Actual Problems of Improving Farming Productivity and Agroecology" (IPFA 2024), E3S Web Conf., vol. 538, Art. no. 04010, 2024, [Online]. Available: https://doi.org/10.1051/e3sconf/202453804010.