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IoT BASED LEAF DISEASE IDENTIFICATION SYSTEM

An IoT Based solution for accurate prediction of plant diseases

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Abstract: Agricultural productivity is often threatened by plant diseases, which, if undetected, can lead to severe yield losses. This paper presents an IoT-based Plant Leaf Disease Identification System, specifically designed to detect diseases in banana, potato, and tomato crops. The system integrates hardware-based detection for banana leaves using a TCS34725 color sensor, which identifies Black Sigatoka, Yellow Sigatoka, and Streak Virus based on color variations. Additionally, a machine learning model, utilizing a DenseNet CNN network, is employed to classify diseases in potato and tomato leaves with an accuracy of 88-90 percent.The system leverages an Arduino Uno, ESP8266 for data transmission, and an LED display for on-device alerts. The Blynk platform is used for real-time monitoring, allowing farmers to receive early disease alerts and take preventive measures. By enabling timely intervention, this solution aims to enhance crop health, yield, and economic stability in the agricultural sector. The results demonstrate a highly effective and accessible approach to plant disease detection, making it a valuable tool for modern precision farming.

Index Terms - IoT, Machine Learning, CNN, Agriculture, Smart Farming, Disease Monitoring.

I. INTRODUCTION

Over the last century, the integration of IoT technology into healthcare has opened new possibilities for disease detection and monitoring. One such innovation is a disease identification system using Arduino. This system is designed to provide a cost-effective, portable, and user-friendly solution for early disease diagnosis. By leveraging real-time data processing and remote monitoring, it offers a reliable way to track health conditions and alert farmers of potential medical issues in plants.[1] At the core of this system is the Arduino microcontroller, which collects data from a color sensor that detects variations in sample colors. These color changes can indicate different health conditions [2].The ESP8266 Wi-Fi module transmits the sensor readings to the Blynk platform, where the data is analyzed and displayed in an intuitive mobile application. This setup allows farmers to monitor results conveniently from their smartphones. The Blynk platform enhances the system by providing real-time updates, remote access, and alert notifications when abnormal readings are detected. This makes it particularly useful for individuals in remote areas.The system's affordability and ease of use make it an excellent tool for enabling early intervention before conditions become severe. [3]. By leveraging IoT for real-time monitoring and ML for image-based disease classification, this system provides a powerful tool for precision farming.

The color sensor plays a crucial role in detecting variations in leaf color, which can indicate early signs of disease. The sensor captures color data from leaves, which is processed by an Arduino microcontroller and transmitted via the ESP8266 Wi-Fi module to the Blynk platform. Through the Blynk mobile app, farmers can access real-time data, visualize trends, and receive alerts when potential disease symptoms are detected. This IoT-based approach allows for continuous monitoring and reduces the dependency on manual inspections, making disease detection more efficient and accessible. To enhance accuracy, a DenseNet-based machine learning model for disease classification. The model is trained on a dataset of tomato and potato leaves affected by diseases such as early blight, late blight, and bacterial spots. Using image processing and deep learning, the system can automatically classify leaf diseases with high precision. Farmers can upload leaf images via an interface, and the DenseNet model processes these images to provide a diagnosis, helping them take timely preventive measures. This ML-based approach significantly improves the reliability of disease detection compared to traditional visual inspections.

II. LITERATURE REVIEW

Min and Guabo [1] explore Sigatoka leaf diseases of bananas, which are caused by three Mycosphaerella species: M. musicola (yellow Sigatoka), M. fijiensis (black Sigatoka), and M. eumusae (eumusae leaf spot). Yellow Sigatoka was previously reported in South Africa, but its specific causal organism was unknown. In order to tackle this, researchers carried out comprehensive surveys from 1999 to 2001 in five producing regions and collected many leaf samples with Sigatoka-like symptoms. These samples were analyzed morphologically, and monoconidial cultures were isolated to determine the causative pathogens. Molecular verification was done with species-specific primers for M. musicola and M. fijiensis, as well as ITS region sequencing for comparison with known Mycosphaerella species. The research unequivocally proved that M. musicola was the single pathogen that was implicated in yellow Sigatoka symptoms in South Africa, dispelling earlier doubts about the etiology of the disease.

Meder and Fabian [2] present ResTS (Residual Teacher/Student), a deep learning model which is intended to enhance the detection of plant diseases using improved classification as well as visualization. This architecture draws on past Teacher/Student models but adds residual connections and batch normalization to maintain gradients during training, avoid vanishing or exploding gradients, and speed up convergence. ResTS uses two classifiers—ResTeacher and ResStudent—trained in a two-way direction, with the passed-through representation utilized to mark important disease-affected areas in plant images. The model was tested on the PlantVillage dataset with 54,306 images of 14 crop species and reached a higher score than previous models. Likewise, Wang and Ben [3] utilize computer vision to identify maize leaf diseases using 2,000 PlantVillage images. Their method both statistically histogram-based and texture-based features are extracted from images and multi-class disease classification via a support vector machine improves accuracy in discrimination of diseases such as Cercospora leaf spot, common rust, and leaf blight. Lan and Xiannhg [4] introduce an optimized DenseNet architecture for corn leaf disease detection, overcoming the limitation of symptom differentiation in the initial stages. Their strategy uses deep learning to scan disease trends, offering a more accurate way to track crop health and enhance agriculture productivity.

III. TOPOLOGY

3.1.PRINCIPLE OF OPERATION

The banana leaf disease detection system based on IoT works through integrating image processing, color sensing, and IoT connectivity to recognize and track plant diseases in realtime. The ESP32-CAM takes high-resolution images of banana leaves, which are processed to identify visible symptoms such as discoloration and spots. Moreover, the TCS3200 color sensor also senses the red, green, and blue reflectance for evaluating changes in leaf color that signify stress or disease. The two-sensor mechanism enhances detection precision by combining visual and spectral information. The Arduino Uno serves as the control module, which allows for communication between sensors and processing units and also allows for smooth data capture.

When the system identifies a possible disease, the data is sent to an IoT dashboard through Wi-Fi or cloud services for remote monitoring. The dashboard combines deep learning models for disease classification and displays insights in the form of graphs, alerts, and reports. Farmers can access real-time updates, environmental conditions, and suggested interventions to avoid disease spread. A 16x2 LCD display also gives on-site alerts for prompt action. This unified IoT platform allows for effective data-driven decision-making, supporting farmers in optimizing crop health, reducing losses, and improving productivity through timely action [2].

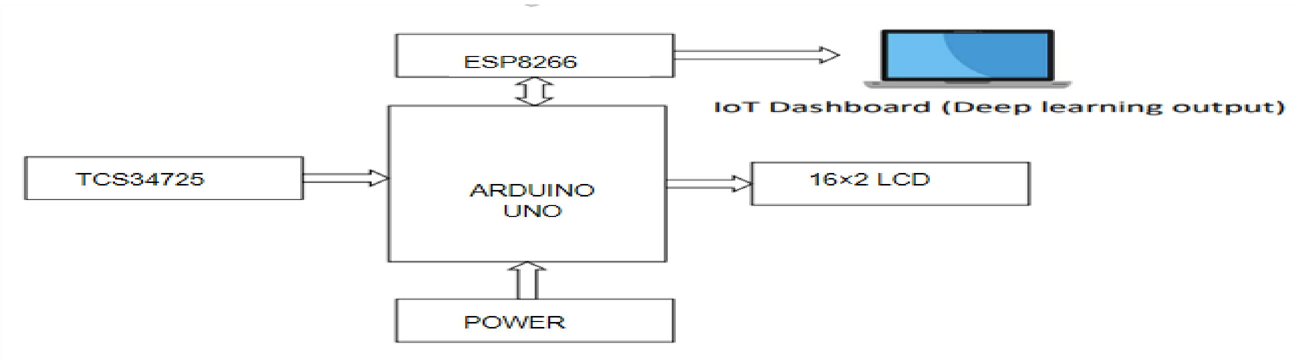


Fig 3.1 Block Diagram of the system

3.2 WORKING

Fig 3.1 represents an IoT-based plant disease detection system that integrates Arduino Uno, ESP8266, a color sensor (TCS34725), a 16×2 LCD display, and an IoT dashboard powered by a deep learning model. The primary function of this system is to analyze leaf color changes and detect potential diseases using sensor-based data collection and AI-driven analysis. The system allows real-time monitoring and provides disease classification through both a local display and a cloud-based dashboard. At the core of the system is the Arduino Uno, which acts as the main controller. It receives data from the TCS34725 color sensor, which detects RGB (Red, Green, and Blue) values of the leaf surface. Changes in these color values can indicate early symptoms of plant diseases. The Arduino processes this color information and sends it to the ESP8266 Wi-Fi module, which enables cloud connectivity for further analysis. The 16×2 LCD display provides a local real-time output of the sensor readings, allowing users to quickly check the condition of the plant without accessing the IoT dashboard.[2]. ESP8266 module plays a crucial role in transmitting the collected sensor data to an IoT-based cloud platform, where a deep learning model (DenseNet) processes the data for accurate disease classification. The IoT dashboard displays the analyzed results, helping farmers make informed decisions about plant health. If a disease is detected, the system provides real-time alerts, enabling farmers to take timely preventive actions. This combination of IoT and AI ensures efficient and automated plant disease monitoring, reducing the need for manual inspections. Overall, this system offers a smart agriculture solution that enhances early disease detection, improves crop yield, and minimizes losses. By integrating sensor-based data collection, IoT-based remote monitoring, and AI-driven deep learning analysis, the system provides an efficient, cost-effective, and accessible method for plant disease detection. Future enhancements could include adding more environmental sensors and refining the machine learning model for increased accuracy, making the system even more robust for agricultural applications.

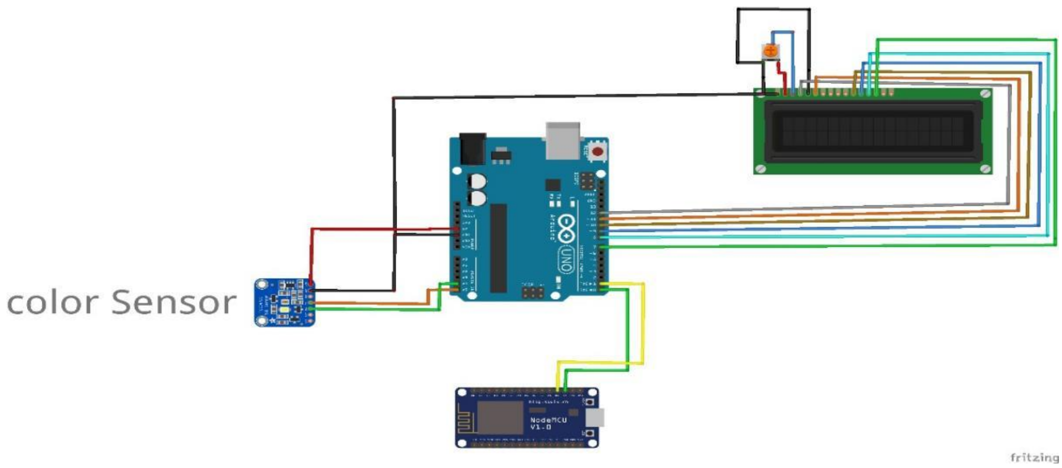


Fig 3.2 Connection Diagram

3.3 COLOUR DISEASE RANGES

Table 3.3 Wavelenth ranges

Diseases	C Values
Black Sigatoka	600nm to 700nm
Yellow Sigatoka	300nm to 400nm
Streak Virus	800nm and above
Healthy Leaf	less than 200nm

The project focuses on mainly three diseases commonly seen in banana leaves[1].The colour sensor consists of photodiodes that convert that measures the intensity of light.The value of intensity is converted into a digital value using 16 bit ADC placed in the colour sensor.Thus the raw value of RGB values are measured .The average of the three is what is called as “C Value”.

3.4 RELATION BETWEEN C VALUE AND DISEASE DETECTED

The value of C as measured by the colour sensor helps to detect the type of disease in banana leaves.For a particular disease there is a upper and lower threshold value.For example black Sigatoka disease happens in the range of 600nm to 700 nm.Therfore when the measured C value comes in this range ,LCD display displays Black Sigatoka disease has been detected.

4.HARDWARE

This section outlines the hardware implementation of the project .

4.1 HARDWARE RESULTS

Connections were done as per the circuit diagram .The leaf samples were collected . All the three diseases were successfully detected by the LCD display

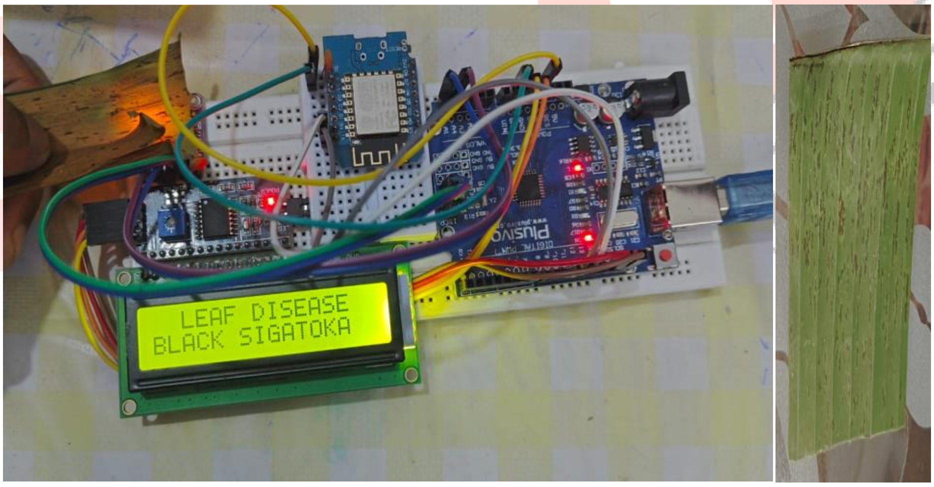


Fig 4.1 Hardware setup of disease detection and sample used

When the value of C value ranges between 600 nm and 700nm as detected by the colour sensor the display displays the particular disease.

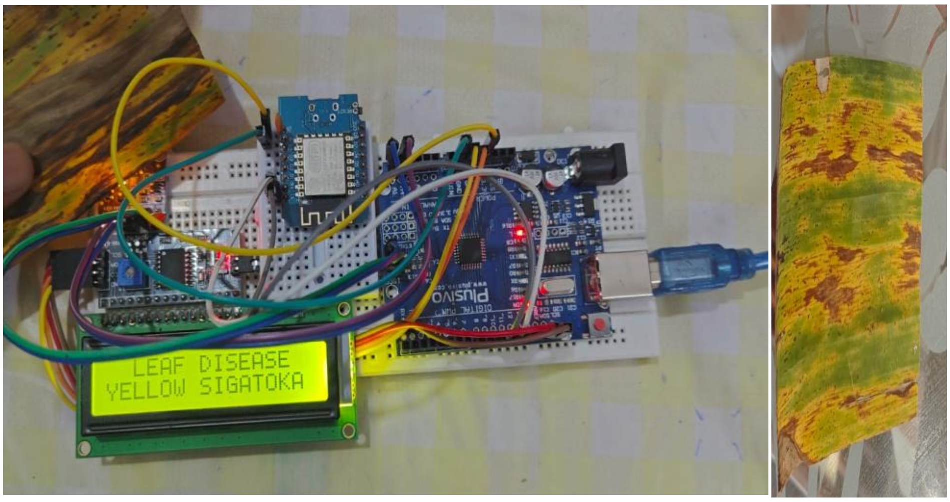


Fig 4.2 Hardware setup of disease detection and sample used

When the value of C ranges between 300nm to 400nm ,Yellow Sigatoka disease is detected.

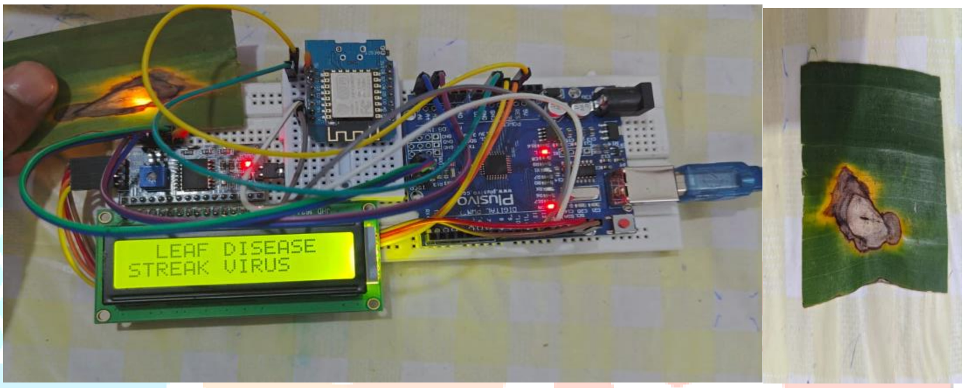
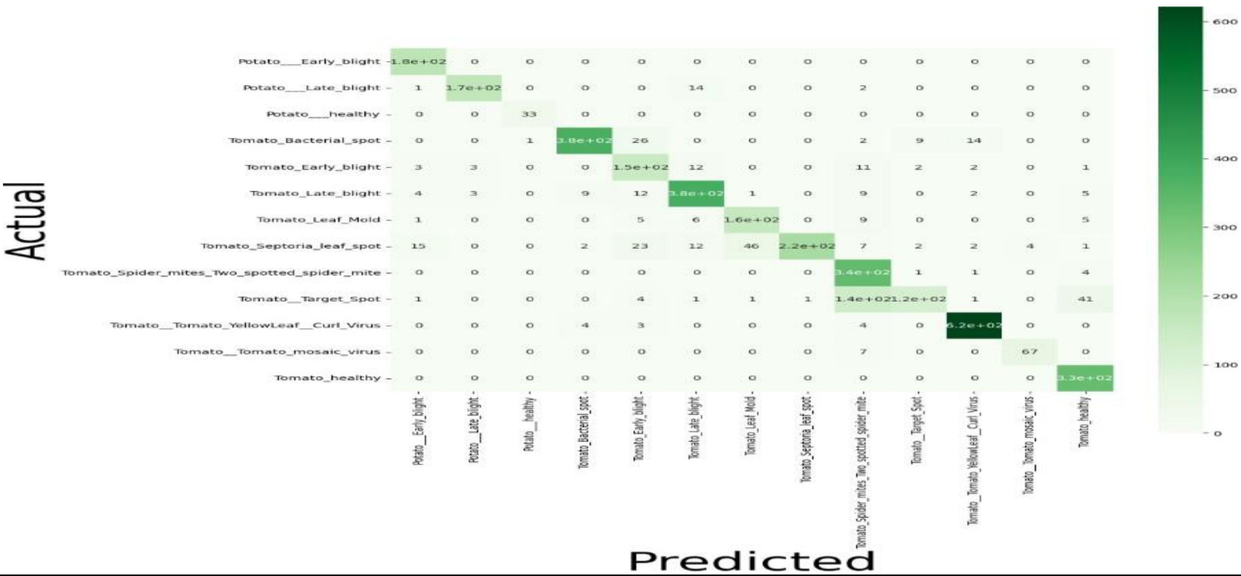


Fig 4.3 Hardware setup of disease detection and sample used

When the value of C ranges between the values 800nm up until 950 nm ,Streak virus can be detected.

5.DEEP LEARNING MODEL ANALYSIS

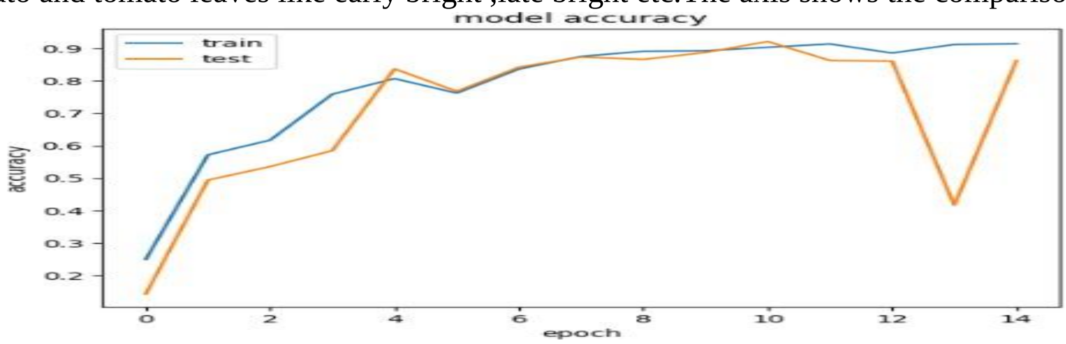
The deep learning component of this IoT-based plant disease detection system is responsible for accurately identifying plant diseases based on leaf images. The system utilizes a DenseNet (Densely Connected Convolutional Network) deep learning model to analyze leaf features such as color, texture, and lesion patterns. This ML-based approach significantly improves disease classification accuracy compared to traditional rule-based color detection.The users capture a photo of a plant leaf using a camera or an IoT-connected device. The image undergoes preprocessing, including noise removal, resizing, and normalization, to enhance its quality before feeding it into the model[4]. The DenseNet architecture then extracts



hierarchical features from the image, identifying disease-specific patterns like brown spots, yellowing, or black lesions.

Fig 5.1 Heat map of the system

The heat map is a graphical representation of the model accuracy.The model is trained to identify different diseases in potato and tomato leaves like early bright ,late bright etc.The axis shows the comparison between



actual and predicted diseases . The

Fig 5.2 Model Accuracy

intensity of the green colour shows the number of samples that have been correctly identified by the model. The model is trained for 15 epochs or iterations .Each epoch means a particular disease.In 13 classes,an average of 300 samples were trained,so in total 4500 samples were collected out of which 3200 samples were trained and 800 were tested.[4].

The model losses have significantly reduced .That means the predicted disease and the actual disease were the same.

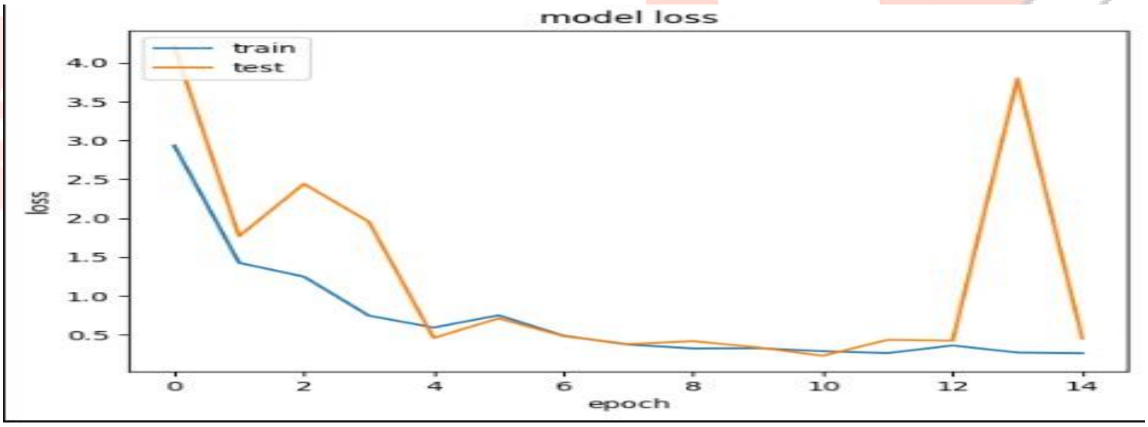


Fig 5.3 Model Loss

6.CONCLUSION

The proposed IoT-based Plant Leaf Disease Detection Sys- tem provides an efficient and consistent solution for banana, potato, and tomato disease detection at early stages. Using hardware-based sensors and machine learning, the system provides precise disease identification, supporting timely in- terventions. The application of the TCS34725 color sensor for detection of banana disease and a DenseNet CNN model for potato and tomato classification facilitates the system to be more accurate and versatile. Besides, the use of IoT technology such as Arduino Uno, ESP8266, and the Blynk platform supports real-time monitoring and notification, which enables farmers to make accurate decisions.Apart from minimizing manual disease detection dependency, the system is an affordable and accessible solution for contemporary precision farming. With minimal crop losses and enhanced disease management, the system supports in- creased yield and financial stability in the farming industry. The outcome proves that fusing machine learning and IoT technologies in plant disease detection has huge potential in transforming farming into higher efficiency and sustainability. Further potential enhancements include boosting the model database for improved precision, integrating new crop species, and enhancing system optimization for larger-scale use..

References

[1] KA. E. Jayasinghe , D.N. Nguyen, T.M.A. Wijaya, C.A. Cañadas, M.A. Malik, and N.A. Rahimi "Review on Li-ion Battery Parameter Extraction Methods," in IEEE Access, vol. 11, pp. 73180-73197, 2023.
[2] P. G. Zadeh , M.H. Ahmadi, S.H. Hosseini, A.H. Golestan, H.M. Nikouyan, and M.R. Kolahgar ''Electrochemical modeling of a thermal management system for cylindrical lithium-ion battery pack considering battery capacity fade,'' Case Stud. Thermal Eng, vol. 32, Apr. 2022, Art. no. 101878.
[3] B.V.Ratnakumar, A.V. Verma, S. Surampudi, and M. Allam "Electrochemical impedance spectroscopy and its applications to lithium ion cells," Seventeenth Annual Battery Conference on Applications and Advances. Proceedings of Conference (Cat. No.02TH8576), Long Beach, CA, USA, 2002.
[4] Eltoumi , Ghannouchi and Bouzidi "Experimental Identification using Equivalent Circuit Model for Lithium-Ion Battery". 2017 IEEE Conference on Control Technology and Applications (CCTA).
[5] N. A. Chaturvedi, R. Klein, J. Christensen, J. Ahmed, and A. Kojic, ''Algorithms for advanced battery-management systems,'' IEEE Control Syst. Mag., vol. 30, no. 3, pp. 49–68, Jun. 2010.