International Journal of Computer and Communication Technology

Volume 9
Issue 1 *Research on Computing and Communication Sciences.*

Article 6

July 2023

# Challenges and Solution for Identification of Plant Disease Using Machine Learning & IoT

Suprava Ranjan Ranjan Laha Mr.
*Siksha 'O' Anusandhan University, Bhubaneswar, Odisha, India*, supravalaha@gmail.com

Sonali Samal
*National Institute of Technology Meghalaya*, p21cs002@nitm.ac.in

Debasish Swapnesh Kumar Nayak
*Siksha 'O' Anusandhan University*, swapnesh.nayak@gmail.com

Saumendra Pattnaik
*Siksha 'o' Anusandhan University*, saumendrapattnaik@soa.ac.in

Binod Kumar Pattanayak Prof. (Dr.)
*Siksha 'O' Anusandhan University*, binodpattanayak@soa.ac.in



## Recommended Citation

Laha, Suprava Ranjan Ranjan Mr.; Samal, Sonali; Nayak, Debasish Swapnesh Kumar; Pattnaik, Saumendra; and Pattanayak, Binod Kumar Prof. (Dr.) (2023) "Challenges and Solution for Identification of Plant Disease Using Machine Learning & IoT," *International Journal of Computer and Communication Technology*: Vol. 9: Iss. 1, Article 6.
DOI: 10.47893/IJCCT.2023.1441
Available at: https://www.interscience.in/ijcct/vol9/iss1/6

# Challenges and Solution for Identification of Plant Disease Using Machine Learning & IoT


Suprava Ranjan Laha[1]
*Department of Computer Science & Engineering*
*ITER, Siksha 'O' Anusandhan University*
Bhubaneswar, Odisha, India
supravalaha@gmail.com

Sonali Samal[2*]
*Department of Computer Science & Engineering*
*[2]National Institute of Technology, Meghalaya, Shillong, India*
p21cs002@nitm.ac.in

Debasish Swapnesh Kumar Nayak[3]
Department of Computer Science & Engineering
ITER, Siksha 'O' Anusandhan University
Bhubaneswar, Odisha, India
swapnesh.nayak@gmail.com

Saumendra Pattnaik[4]
Department of Computer Science & Engineering
ITER, Siksha 'O' Anusandhan University
Bhubaneswar, Odisha, India
saumendrapattnaik@soa.ac.in

Binod Kumar Pattanayak[5]
*Department of Computer Science & Engineering*
*ITER, Siksha 'O' Anusandhan University*
Bhubaneswar, Odisha, India
binodpattanayak@soa.ac.in



***Abstract*—Internet of Thing (IoT) is a groundbreaking technology that has been introduced in the field of agriculture to improve the quality and quantity of food production. As agriculture plays a vital role in feeding most of the world's population, the increasing demand for food has led to a rise in food grain production. The identification of plant diseases is a critical task for farmers and agronomists as it enables them to take proactive measures to prevent the spread of diseases, protect crops, and maximize yields. Traditional methods of plant disease detection involve visual inspections by experts, which can be time-consuming and often subject to human error. However, with advancements in technology, the use of IoT and Machine Learning (ML) has emerged as a promising solution for automating and improving plant disease identification. This paper explores the challenges and solutions for the identification of plant diseases using IoT and ML. The challenges discussed include data collection, data quality, scalability, and interpretability. The solutions proposed include the use of sensor networks, data pre-processing techniques, transfer learning, and explainable AI.**



**Keywords— IoT, Machine Learning, Plant Disease, Sensor Network.**


## I. INTRODUCTION

Plant diseases pose a significant threat to global food security, causing losses of up to 40% in crop yields annually [1, 2]. Early detection and accurate identification of plant diseases are essential for effective disease management and control. Traditional methods of plant disease detection involve visual inspections by experts, which can be time-consuming and often subject to human error [3]. With advancements in technology, IoT and ML have emerged as promising solutions for automating and improving plant disease identification [4, 5]. Agriculture plays a critical role in the economic growth of developing countries, as it is a significant source of income. In India, cultivation is the primary source of income, and about 70% of the population depends on farming directly or indirectly for their economic well-being [6]. Agriculture also creates essential employment opportunities in the Indian economy, and approximately 70% of people's livelihoods depend on it. Inefficiency and lack of management are the root causes of agricultural problems. The quality of farming products is as important as their quantity, but traditional farming methods often result in low productivity. Agriculture is heavily dependent on weather conditions, soil fertility, and disease prevention. Researchers are now exploring the use of IoT to automate the disease identification process of plants, which can help prevent disease at an early stage. Environmental impact is also an important factor to consider in enhancing agricultural productivity [7]. To improve management and decision-making tasks, large-scale observation facilitated by remote sensing technology can provide a wide-view image of the farming environments [8, 9]. The remote sensing technology produces a considerable amount of image data that can be used for analyzing and identifying various diseases in plants. Image analysis is an important research area in agriculture that can aid in identifying and classifying diseases. To collect and analyze data, IoT implements sensors that can capture images and sensed data. Popular classification techniques like Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-NN, Wavelet-based Filtering, and Regression Analysis can be used to identify diseases from the collected data. The identification of plant diseases is crucial in agriculture, and it is essential for the development of smart farming applications. The general flow of techniques involved in the identification process is depicted in Figure 1.

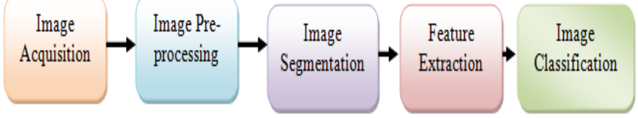


Figure 1: Plant disease Identification System

## II. RELATED WORK

Plant diseases can often be identified by visible symptoms on leaves, stems, flowers, or fruits. Each disease has a unique visible pattern that experts can recognize. However, identifying diseases through laboratory testing of infected samples can be expensive and time-consuming. Therefore, IoT can be used to provide real-time information to farmers to prevent crops from being affected by diseases. To improve agriculture, there has been a significant amount of research aimed at developing new methods and technologies. Nandhini et al. proposed a method for automatic disease detection and classification using IoT and Compressed Sensing (CS) technology. The proposed method, called WEDDS, achieved an accuracy of 98.5% and 98.4% in disease detection and classification, respectively [10]. Kale et al. [11] developed an automated Smart Farming system that uses IoT and an improved genetic algorithm-based Extreme learning machine (ELM) classifier called IGA-ELM. The algorithm selects 34.5% to 45.26% of unique features, resulting in a 5.71% improvement in accuracy in the classification report with the use of only a minimum of 27.27% features. Khattab et al. [12] implemented a precision agriculture survey using an IoT-based monitoring system. The authors focused on detecting two common diseases, early blight and late blight, in potatoes and tomatoes. They applied an artificial intelligence algorithm that can mimic the decision-making process of a human expert in identifying plant diseases. The system achieved a high accuracy rate in disease detection and provided real-time alerts to farmers. The paper by Thorat et al. proposes an IoT-based system that uses image processing to identify plant diseases. The system utilizes smart sensors like soil moisture, temperature, and humidity in the field [13]. K-means methodology is applied for disease identification, including black spot, botrytis blight, leaf spot, and powdery mildew. The system establishes wireless communication and an interface for easy access. Summary of the above few papers are shown in Table I.

Table 1: Summary of few research work done on Plant disease detection system

| Authors & Year | Technique Used | Dataset Used | Findings |
|---|---|---|---|
| Kalvakolanu et al (2021) [14] | ResNet34 and ResNet50 | Potato, Tomato, Pepper bell | The authors of the study achieved an accuracy of 99.44% using ResNet34 and ResNet50 models with a dataset of over 4000 images. They also compared the use of RGB and grayscale images for plant disease detection and were able to identify 13 diseases from healthy leaves. |
| Militante et.al (2019) [15] | CNN | Tomato, grapes, corn, apple, sugarcane | Discusses the application of machine learning for detecting plant diseases across multiple plant varieties such as apples, corn, grapes, potato, sugarcane, and tomato. The system was able to achieve a high accuracy rate of 96.5% and can be used for real-time disease detection. |
| Bhise et.al (2022) [16] | CNN | Various Plant leaves | The paper concludes that the use of deep learning-based plant disease detection techniques is effective in accurately identifying plant leaf diseases with the help of sufficient training data and various techniques like data augmentation and transfer learning. |
| Pawar et.al (2022) [17] | CNN | Tomato, grapes, corn, apple, sugar cane | This paper presents a convolutional neural network (CNN)-based system for accurate detection of plant diseases. The system achieves a high accuracy rate of up to 93% in disease detection and provides farmers with weather forecasting information to assist them in making informed decisions. The authors also suggest that the system can be extended to detect diseases in various other plants.Top of Form |
| Dheeraj et.al (2022) [18] | EfficientNetB1 | Pepper , Potato , Tomato | The research demonstrates the successful utilization of transfer learning technique through the EfficientNetB1 model, achieving a remarkable accuracy rate of 99.335% for detecting leaf diseases. The next step could involve the development of a mobile application utilizing the proposed algorithm to enable early-stage detection of leaf diseases, which can prevent potential crop damage. |

## III. PLANT DISEASE DETECTION USING IOT

Identification of plant disease using IoT involves the use of sensors and other connected devices to monitor and collect data on various environmental factors that affect plant health, such as temperature, humidity, soil moisture, and light levels. The collected data is then analyzed using machine learning algorithms to identify patterns and detect any signs of disease or stress in the plants. One common approach in IoT-based plant disease identification is to use image analysis to detect visual symptoms of diseases in plant leaves. Cameras or other imaging devices are used to capture images of the leaves, which are then processed using machine learning algorithms to identify any signs of disease, such as discoloration, spots, or other irregularities. Other IoT-based approaches may use data from various sensors to detect changes in plant physiology or biochemistry that may be indicative of disease. For example, changes in the levels of certain plant hormones or metabolites can signal the presence of disease, and sensors can be used to monitor these changes and alert farmers or researchers to potential issues.

Overall, IoT-based approaches to plant disease identification offer a powerful tool for improving crop management and productivity, allowing farmers to quickly identify and respond to emerging issues and reduce the need for costly and environmentally harmful chemical treatments.

## IV. IDENTIFICATION OF PLANT DISEASE USING MACHINE LEARNING

Identification of plant diseases using machine learning is a cutting-edge research area that has gained significant attention in recent years. With the increasing population and the growing demand for food, there is a need to ensure that plant diseases are detected early enough to prevent crop losses. Traditional methods of plant disease diagnosis are time-consuming, expensive, and often require expert knowledge. However, machine learning techniques have the potential to revolutionize the field of plant pathology by providing faster and more accurate methods for detecting plant diseases.

Machine learning algorithms can be used to identify patterns in large datasets of plant images and provide accurate predictions of the diseases affecting the plant. The process involves collecting images of the plants and using these images to train the machine learning model. Once trained, the model can be used to analyze new images and make predictions about the presence of diseases. The accuracy of the model is often improved by incorporating additional information, such as climate data, soil conditions, and plant genetics.

Several machine learning algorithms have been used for plant disease identification, including deep learning algorithms, support vector machines, and random forest classifiers. Deep learning algorithms, such as convolutional neural networks, have been particularly successful in image recognition tasks and have shown promising results in plant disease identification. These algorithms are capable of automatically learning the relevant features from the images and using them to make accurate predictions.

One of the main advantages of machine learning-based plant disease identification is that it can be used in conjunction with Internet of Things (IoT) technology to provide real-time monitoring of plant health. IoT devices, such as sensors and cameras, can be deployed in the field to collect data on plant health and transmit it to a central server for analysis. This approach allows for the early detection of diseases and the implementation of timely interventions to prevent crop losses.

However, plant disease identification using machine learning is a rapidly developing field with significant potential for improving crop yields and reducing losses due to diseases. The use of machine learning algorithms, coupled with IoT technology, provides a promising approach for real-time monitoring and early detection of plant diseases. Further research is needed to refine the algorithms and improve their accuracy, but the potential benefits make this a highly valuable area of study.

## V. MACHINE LEARNING BASED CLASSIFICATION OR RECOGNITION TECHNIQUES

Machine learning (ML) based classification or recognition techniques have emerged as a popular approach for identifying plant diseases. In this approach, the ML algorithms are trained using a dataset of images of healthy and infected plants to recognize and classify the diseases. One of the commonly used ML techniques for plant disease identification is the Convolutional Neural Network (CNN). CNNs are particularly effective in analyzing image data and have shown promising results in identifying plant diseases. They work by extracting features from images at different levels of abstraction, allowing for more accurate disease recognition. Another popular ML technique for plant disease identification is Support Vector Machines (SVM). SVMs work by identifying patterns in the data and classifying them based on those patterns. SVMs have been used successfully in identifying plant diseases, especially in cases where the dataset is relatively small.

Other ML techniques such as Random Forests, Decision Trees, and Naive Bayes have also been used for plant disease identification. These techniques work by building a model that can predict the class of the input image based on a set of features extracted from the image. Overall, ML-based classification or recognition techniques have shown great promise in identifying plant diseases and can potentially help improve crop yields by enabling early detection and prevention of diseases.

## VI. CHALLENGES FOR PLANT DISEASE DETECTION

1. Data Collection: One of the biggest challenges in using IoT and ML for plant disease identification is the collection of accurate and reliable data. This requires the deployment of sensor networks in the field, which can be costly and time-consuming.
2. Data Quality: Another challenge is ensuring the quality of the collected data. The data collected may be noisy, incomplete, or biased, which can affect the accuracy of the ML models.
3. Scalability: As the number of crops and diseases increases, the ML models need to be scalable to handle the growing data volume.
4. Interpretability: The output of the ML models may not be easily interpretable, making it challenging for farmers and agronomists to understand and take action based on the results.

## VII. SOLUTIONS FOR PLANT DISEASE DETECTION

1. Sensor Networks: One solution to overcome the data collection challenge is the use of sensor networks. These networks can collect data on temperature, humidity, soil moisture, and other environmental factors, which can be used to predict the occurrence of diseases.
2. Data Pre-processing Techniques: To ensure the quality of the collected data, pre-processing techniques such as data cleaning, data normalization and data augmentation can be used to remove noise, fill in missing values, and increase the diversity of the data.
3. Transfer Learning: To address the scalability challenge, transfer learning can be used to leverage pre-trained models to classify new diseases and crops, reducing the need for large amounts of labeled data.
4. Explainable AI: To improve the interpretability of the ML models, explainable AI techniques can be used to provide explanations for the decisions made by the model, making it easier for farmers and agronomists to understand and take action based on the results.

## VIII. ANALYSIS & RECOMMENDATION

The use of machine learning and IoT for plant disease identification has shown promising results in recent years. By utilizing sensors and image analysis techniques, it is possible to detect diseases early and take preventative measures to improve crop yield and reduce economic losses. One of the key benefits of using machine learning and IoT for plant disease identification is the ability to process large amounts of data quickly and accurately. This can enable real-time monitoring of crops and early detection of diseases, which is crucial for timely intervention. Machine learning algorithms such as artificial neural networks, support vector machines, and k-nearest neighbors can be used for image classification and disease identification, and can achieve high accuracy rates. Another advantage of using machine learning and IoT for plant disease identification is the ability to monitor environmental factors such as temperature, humidity, and soil moisture levels. By analyzing these factors along with image data, it is possible to develop a comprehensive understanding of crop health and identify potential disease triggers. However, there are also some limitations to using machine learning and IoT for plant disease identification. One challenge is the cost of implementing the necessary sensors and infrastructure, which can be prohibitively expensive for small-scale farmers. Additionally, the accuracy of machine learning models can be impacted by factors such as lighting conditions, image quality, and variations in plant appearance. Overall, the use of machine learning and IoT for plant disease identification has significant potential to improve crop yield and reduce economic losses. However, it is important to carefully consider the costs and limitations of these technologies before implementing them on a large scale.

Based on the research and analysis, it is recommended that the following steps be taken for the effective identification of plant disease using machine learning and IoT:

1. Selection of appropriate sensors: The first step is to select the appropriate sensors that can capture accurate data related to plant health. Sensors can include spectral sensors, imaging sensors, and physical sensors such as temperature and humidity sensors.
2. Data collection and storage: The data collected from the sensors needs to be stored in a centralized database for analysis. Cloud-based platforms can be used for efficient data storage and management.
3. Data preprocessing: The collected data needs to be preprocessed to remove any noise or outliers that may affect the accuracy of the analysis. Techniques such as data cleaning, data transformation, and feature selection can be used for data preprocessing.
4. Machine learning model selection: Several machine learning models such as Artificial Neural Networks, Support Vector Machines, K-NN, and Random Forest can be used for disease classification. The selection of the appropriate model will depend on the nature and complexity of the data.
5. Training and testing: The machine learning model needs to be trained using labeled data, and the accuracy of the model needs to be tested using unseen data.
6. Deployment: Once the model is trained and tested, it can be deployed to the field for real-time disease identification. IoT devices can be used to transmit the data from the field to the centralized database for analysis.
7. Alert system: An alert system can be developed to notify farmers in real-time about the presence of disease in their crops. This will enable farmers to take preventive measures such as spraying pesticides, removing infected plants, and adjusting irrigation levels.

By following these steps, farmers can effectively identify and prevent diseases in their crops, leading to increased productivity and reduced crop losses.

Quantitative and qualitative research has been conducted in the field of plant disease identification using IoT and Machine Learning techniques. Table 2 is presented as a summary of the research carried out using these methods. Analyzing the scholarly literature trends over a six-year period (2018-2023) in the Scopus database can provide valuable insights for engineers and researchers working on plant disease detection. Extrapolations based on publication statistics can help predict future trends in this area.

Table 2: Research contribution using IoT & ML for Plant disease Identification

| Year | Plant disease detection using ML | Plant disease detection using IoT |
|---|---|---|
| 2018 | 42 | 12 |
| 2019 | 103 | 18 |
| 2020 | 134 | 31 |
| 2021 | 260 | 46 |
| 2022 | 431 | 67 |
| 2023 | 149 | 29 |

An interesting finding that research on IoT for identification of plant diseases has been found to be relatively less than the machine learning techniques used for detection. However, it is important to note that IoT has the potential to significantly improve the accuracy and speed of disease identification in plants, as well as reduce the need for manual labor. As such, further research and development in this area could lead to significant advancements in the growth of the agricultural field.

Based on the information provided, Figure 2 illustrates the research trends in plant disease detection using two main categories, namely machine learning and IoT techniques. The trend line in the graph indicates that there is a lot of research using Machine learning techniques as compared to IoT techniques. However, the combination of IOT and machine learning can provide a powerful tool for early detection and prevention of plant diseases, leading to improved crop yields and reduced costs for farmers.

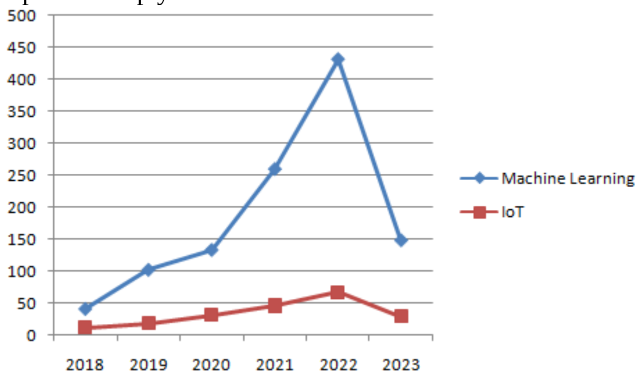


Figure 2: Trends of Plant disease Identification

## IX. CONCLUSION

IoT and ML have the potential to revolutionize the way plant diseases are detected and managed. However, several challenges need to be addressed to ensure the effectiveness of these solutions. By deploying sensor networks, using pre-processing techniques, leveraging transfer learning, and incorporating explainable AI, we can improve the accuracy, scalability, and interpretability of the ML models, enabling farmers and agronomists to take proactive measures to prevent the spread of diseases, protect crops, and maximize yields. Both ML and IoT are emerging as important technologies for plant disease detection. ML-based approaches have witnessed a faster growth rate and higher number of publications compared to IoT-based approaches. However, it is worth noting that these trends may change in the future as new technologies and research methods emerge.

## REFERENCES


[1] N., De, D., & Hussain, I. (2018). Internet of Things (IoT) for smart precision agriculture and farming in rural areas. *IEEE Internet of Things Journal*, *5*(6), 4890-4899.

[2] Pattnaik, S., Banerjee, S., Laha, S. R., Pattanayak, B. K., & Sahu, G. P. (2022). A Novel Intelligent Street Light Control System Using IoT. In Intelligent and Cloud Computing: Proceedings of ICICC 2021 (pp. 145-156). Singapore: Springer Nature Singapore.

[3] Pattnaik, S., Laha, S. R., Pattanayak, B. K., & Pattanaik, B. C. (2021, January). A Framework to Detect Digital Text Using Android Based Smartphone. In 2021 1st Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON) (pp. 1-6). IEEE.

[4] Laha, S. R., Mahapatra, S. K., Pattnaik, S., Pattanayak, B. K., & Pati, B. (2021). U-INS: an android-based navigation system. In Cognitive Informatics and Soft Computing: Proceeding of CISC 2020 (pp. 125-132). Springer Singapore.

[5] Mohapatra, A., Pattnaik, S., Pattanayak, B. K., Patnaik, S., & Laha, S. R. (2022). Software Quality Prediction Using Machine Learning. In Advances in Data Science and Management: Proceedings of ICDSM 2021 (pp. 137-146). Singapore: Springer Nature Singapore.

[6] Samal, S., Nayak, R., Jena, S., & Balabantaray, B. K. (2023). Obscene image detection using transfer learning and feature fusion. Multimedia Tools and Applications, 1-29.

[7] Laha, S. R., Pattanayak, B. K., & Pattnaik, S. (2022). Advancement of Environmental Monitoring System Using IoT and Sensor: A Comprehensive Analysis. AIMS Environmental Science, 9(6), 771-800.

[8] Mahapatra, A. K., Panda, N., & Pattanayak, B. K. (2023). Quantized Salp Swarm Algorithm (QSSA) for optimal feature selection. International journal of information technology, 15(2), 725-734.

[9] Mahakud, R., Pattanayak, B. K., & Pati, B. (2022). Internet of things and multi-class deep feature-fusion based classification of tomato leaf disease. Indones. J. Electr. Eng. Comput. Sci, 25(2), 995-1002.

[10] Aasha Nandhini, S., Hemalatha, R., Radha, S., & Indumathi, K. (2018). Web enabled plant disease detection system for agricultural applications using WMSN. Wireless Personal Communications, 102, 725-740.

[11] Kale, A. P., & Sonavane, S. P. (2019). IoT based Smart Farming: Feature subset selection for optimized high-dimensional data using improved GA based approach for ELM. Computers and Electronics in Agriculture, 161, 225-232.

[12] Khattab, A., Habib, S. E., Ismail, H., Zayan, S., Fahmy, Y., & Khairy, M. M. (2019). An IoT-based cognitive monitoring system for early plant disease forecast. Computers and Electronics in Agriculture, 166, 105028.

[13] Ghosh, D. K., Bhose, S., Sharma, P., Warghane, A., Motghare, M., Ladaniya, M. S., & Yadav, A. (2017). First report of a 16SrXIV group phytoplasma associated with witches'-broom disease of acid lime (Citrus aurantifolia) in India. Plant Disease, 101(5), 831-831.

[14] Murali, V., & Akhilkumar, K. S. (2022). Plant Disease Recognition and Crop Recommendation System using Deep Learning. In 2022 1st International Conference on Computational Science and Technology (ICCST) (pp. 543-548). IEEE.

[15] Militante, S. V., Gerardo, B. D., & Dionisio, N. V. (2019). Plant leaf detection and disease recognition using deep learning. In 2019 IEEE Eurasia conference on IOT, communication and engineering (ECICE) (pp. 579-582). IEEE.

[16] Patil, S. A., Kumbhar, P. D., Satvekar, B. S., Harale, N. S., Bhise, S. C., Patil, S. K., ... & Anuse, M. A. (2022). Adsorption of toxic crystal violet dye from aqueous solution by using waste sugarcane leaf-based activated carbon: isotherm, kinetic and thermodynamic study. Journal of the Iranian Chemical Society, 19(7), 2891-2906.

[17] Pawar, A. B., Jawale, M. A., William, P., Chhabra, G. S., Rakshe, D. S., Korde, S. K., & Marriwala, N. (2022). Implementation of blockchain technology using extended CNN for lung cancer prediction. Measurement: Sensors, 24, 100530.

[18] Dheeraj, G., Anumala, P. K., Sagar, L. R., Krishna, B. V., & Bala, I. (2022). Plant Leaf Diseases Identification using Deep Learning Approach for Sustainable Agriculture. In 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS) (pp. 1429-1434). IEEE.