Crop Production Prediction Using Ensemble Neural Network Model

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ABSTRACT

This study presents a pioneering methodology for predicting and classifying crop production, leveraging anEnsembled Neural Network Model (ENNM) that integrates the Squeeze Net and Efficient Net architectures. By amalgamating the strengths of these models, our approach aims to significantly enhance the accuracy and efficiency of crop production forecasting. Squeeze Net's lightweight design and Efficient Net's superior performance collectively contribute to a robust framework capable of tackling the complexities of agricultural data. Through extensive experimentation on a diverse crop production dataset, we demonstrate the efficacy of our proposed ENNM, achieving an outstanding accuracy rate of 98.5%. It enhances the model's adaptability to diverse agriculturalenvironments and cropping systems. Our findings signify a significant step forward in harnessing advanced machinelearning (ML) techniques for addressing real-world challenges in agriculture, with implications for improving crop yield forecasts, optimizing resource allocation, and bolstering food security efforts on a global scale.

Keywords: Deep Learning (DL), Prediction, Classification, Crop Production, Ensembled Neural Network Model,ENNM, Squeeze Net, Efficient Net.

1 Introduction

Agriculture, the backbone of civilization, has witnessed unprecedented transformation over centuries. From rudimentary farming practices to advanced agricultural technologies, humanity's quest for efficient crop production has been relentless. In the modern era, the convergence of data science, artificial intelligence, and agricultural science has paved the way for predictive analytics in crop production. This fusion has given birth to a revolutionary concept: the prediction of crop production [1] [2]. Forecasting future harvests properly is the essence of agricultural production prediction, which entails using data from a variety of sources such satellite imaging, weather predictions, soil quality evaluations, and historical crop yields. Smarter decision-making, better resource allocation, less risk, andhigher overall production are all possible thanks to this predictive strategy for farmers, agricultural policymakers,and other stakeholders. The advent of satellite technology has been a game-changer in crop production prediction. Satellites equipped with multispectral sensors capture detailed imagery of agricultural landscapes, providing invaluable insights into crop health, growth patterns, and environmental conditions. Crop production holds unparalleled significance in addressing the burgeoning demands of a rapidly growing global population. With projections indicating an increase to 9.7 billion by 2050, the need for sustainable agricultural practices becomes imperative to ensure food security and alleviate hunger. Crop production not only fulfills the nutritional requirements but also serves as a source of livelihood for millions, particularly in rural areas.

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Moreover, it contributes significantly to national economies through exports, trade, and employment opportunities. Therefore, comprehending the classification of crop production is indispensable for devising effective strategies to meet present and future challenges [3] [4] [5]. The classification of crop production is inherently diverse, encompassing various criteria based on geographical, ecological, and technological factors. Geographically, crops are classified based on their suitability to different climatic conditions, soil types, and topographies. Ecologically, they are categorized into various ecosystems, such as tropical, temperate, and arid regions, influencing the selection of crops and cultivation techniques.

One of the key enablers of prediction and classification in crop production is the availability of vast amounts of data from diverse sources. With the advent of advanced sensing technologies, including satellites, drones, and IoT devices, farmers now have access to real-time data on soil moisture, temperature, precipitation, vegetation indices, and more. This wealth of information serves as the foundation for developing sophisticated models and algorithms that can accurately predict crop yields, identify optimal planting conditions, and classify crops with high precision [6] [7]. ML algorithms lie at the heart of many prediction and classification systems incrop production. These algorithms, which include techniques such as random forests, support vector machines, neural networks, and DL, excel at extracting meaningful patterns and relationships from complex datasets. By training on historical data and iteratively refining their predictions, ML models can achieve remarkable accuracy in forecasting yields, diagnosing crop diseases, and classifying crop types.

In this context, this study proposes a novel methodology for predicting and classifying crop production using an ENNM that integrates the Squeeze Net and Efficient Net architectures. Squeeze Net, renowned for its Lightweight design and efficient inference capabilities, is well-suited for resource-constrained environments commonly encountered in agriculture. Meanwhile, Efficient Net represents the state-of-the-art in model efficiency and scalability, offering superior performance across various tasks. By integrating the strengths of both Squeeze Net and Efficient Net within the ENNM framework, our approach aims to enhance the accuracy and efficiency of crop production forecasting.

2 Related Works

Agriculture, the foundation of any economy, contributed significantly to GDP. It was critical to have fruitful and healthy crops if a government was to provide its people with food. Because of land diversions, weather, geographical locations, defensive measures against diseases, and natural disasters, it became increasingly difficult to monitor crops with human involvement. Conventional methods of crop classification and production prediction failed when environmental factors were unfavourable. This research presented a fuzzy hybrid ensemble technique that used remote sensory data for improved remote crop yield estimation and kind's categorization. It took advantage of new precision agricultural technologies for this purpose. Zooming, scaling, flipping, shearing, and fuzzy neighbourhood spatial filtering were some of the ways the architecture improved the combined pictures. Among the ensemble categorization approach that used the bagging strategy, the study found the best weights forthe top candidate classifiers [8]. To get an objective categorization of several crop kinds, such as wheat, sugarcane, jute, and maize, the picture datasets were enhanced. Lentils, rice, sugarcane, flaxseed, and wheat yield estimateswere based on data retrieved from the World Bank DataBank and the United Nations FAO. Ensemble methodology outperformed lowest decision tree method by 24% and highest gradient boosting method by 13% in crop type classification on average. Over the yield years 2017–2021, the gradient boosting predictor outperformed the multivariate regressor, random forest, and decision tree regressor, and it also had the lowest mean square error value.Additional features of the suggested design included support for embedded devices and the ability for distantdevices to use lightweight categorization algorithms like MobilenetV2. With this, processing time and overhead fora big group of pooled photos could be drastically reduced. In agriculture, crop diseases posed a serious risk to harvest success. They had a significant economic impact and caused farmers to suffer large losses. DL frameworks were used to utilize the distinctive traits displayed by diseased leaves to diagnose the illnesses. A multi-crop disease detection model that could categorize agricultural illnesses regardless of crops was proposed in that research using the CCDL framework. An essential building block in that design was the CCB. To control the amount of model parameters, that unit used a point convolution layer placed before each convolution layer. The convolution layers inside the CCB were subjected to a full concatenation route [9]. It improved feature map use and contributed to higher classification accuracy. The restructured Plant Village dataset was used to train the suggested architecture. After training, a model termed a PCCDL was applied to reduce the model size.

The model PCCDL with PCCDL-PSCT beat the other two variations of this suggested architecture, achieving a greater categorization accuracy of 98.14% with a smaller model size of around 10 MB.Higher yields were the consequence of modern agricultural practices that took into account factors such as soil quality, water and fertilizer requirements, and crop monitoring at each stage of a plant's life cycle. In addition, data collecting and monitoring devices that were compatible with the IoT aided in the detection of agricultural illnesses and the reproductive state of harmful pests. Obtaining information from samples taken at various points throughout the crop's life cycle confirmed the existence of a likely connection between meteorological variables, harvest success, and insect offspring. The environmental parameters that supported the greater insect breeding conditions were identified through data analysis performed on data acquired through an IoT monitoring device. Using these meteorological characteristics, the knowledge base of the proposed fuzzy inference system was constructed [10]. Fuzzy criteria were employed by the multi-objective evolutionary algorithm to determine an appropriate cropping window and breeding circumstances with low pest populations. Using an IoT sensor network monitoring infrastructure provided by IEEE 802.15.4 in medium grass vegetation, this concept found crop-sowing windows based on fuzzy logic with optimum crop production and lowest insect development. Crops of sugarcane and rice were the subjects of these trials. Research took place in Gwalior, Madhya Pradesh, India, in an agricultural setting. The field-deployed WSN collected data on soil moisture, rainfall, temperature, and more. In order to assist farmers, achieve optimum harvests, IoT application development services used fuzzy logic to identify the best times to sow crops, therefore preventing insect development.

3 Proposed Model

Model Architecture plays a pivotal role in the development of predictive models, especially in domains likeagriculture where accurate forecasts can have significant impacts on crop yield, resource allocation, and food security. In this context, the implementation of an ENNM comprising SqueezeNet and EfficientNet architectures holds promise for enhancing the accuracy and efficiency of crop production prediction. SqueezeNet stands out in the landscape of convolutional neural network (CNN) architectures for its innovative design principles focused on minimizing model size and computational complexity while preserving performance. This unique characteristic makes SqueezeNet an ideal candidate to serve as a foundational component within the ENNM for crop production prediction. One of the primary motivations behind the development of SqueezeNet was to address the growing demand for deploying DL models on resource-constrained devices, such as edge computing platforms and Internet of Things (IoT) devices prevalent in agricultural settings. These environments typically have limited computational resources, memory, and power constraints, posing significant challenges for deploying complex models like traditional CNNs. SqueezeNet architecture typically consists of convolution layers, followed by fire modules, and finally global average pooling and softmax layers. Let's denote the output of the SqueezeNet model as Where represents the input features, represents the parameters of the fire modules, represents the parameters of the softmax layer. By leveraging these techniques, SqueezeNet achieves a remarkable reduction in model size and computational complexity without compromising performance. This makes it an attractive choice for deploying DL models in resource-constrained environments commonly encountered in agricultural applications. Whether deployedon edge devices for real-time monitoring of crops or integrated into IoT platforms for smart agriculture solutions, SqueezeNet's lightweight and efficient design make it well-suited for driving innovation and efficiency in agricultural practices. EfficientNet, introduced by Tan et al. in 2019 [11], stands as a groundbreaking advancement in the realm of DL architecture, epitomizing unparalleled efficiency and scalability. Its innovative approach, rooted in the concept of compound scaling, has redefined the landscape of convolutional neural networks (CNNs), offering a paradigm shift in model design principles. The cornerstone of Efficient Net's success lies in its novel compound scaling method, which orchestrates a harmonious balance between model depth, width, and resolution. Traditionally, CNN architectures were scaled by independently adjusting these dimensions, often leading to suboptimal performance or excessive computational costs. However, Efficient Net introduces a systematic and principled approach to scaling, wherein each dimension is scaled in proportion to the others, ensuring optimal utilization of computational resourcesand model capacity. Efficient Net architecture consists of multiple blocks (MBConv blocks) repeated multiple times, each containing convolutional layers, squeeze-and-excitation blocks, and skip connections. Let's denote the output of the Efficient Net model as. Where represents the input features, represents the parameters of the MBConv blocks.

4 Results and Discussions

The proposed model harnesses the capabilities of both SqueezeNet and EfficientNet within the ENNM framework. The working principle of the proposed model revolves around the integration of SqueezeNet and EfficientNet architectures within the ENNM framework. At its core, the model operates by leveraging the unique strengths of each architecture to enhance the accuracy and efficiency of crop production prediction and classificationtasks SqueezeNet, renowned for its lightweight design and efficient inference capabilities, forms the foundation of the ENNM. By employing techniques such as 1x1 convolutions and aggressive down sampling, SqueezeNet minimizes model size and computational complexity without compromising performance. This makes it particularly well-suitedfor deployment in resource-constrained environments, such as agricultural settings where computational resources may be limited. EfficientNet represents the state-of-the-art in model efficiency and scalability. Developed through a principled approach to scaling model depth, width, and resolution, EfficientNet achieves superior performance across various tasks while maintaining computational and parameter efficiency. By incorporating EfficientNet into the ENNM framework, the model gains access to advanced features and representations, further enhancing its predictive capabilities. The integration of SqueezeNet and EfficientNet within the ENNM framework follows an ensemble learning approach. Ensemble learning combines the predictions of multiple models to improve overall performance and robustness. In this case, the ENNM aggregates the predictions of SqueezeNet and EfficientNet models to make afinal prediction. By leveraging the complementary strengths of both architectures, the ENNM achieves moreaccurate and reliable predictions than either model alone.

Table 1: Proposed Model Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ENNM (SqueezeNet)	98.11	95.2	97.5	96.33
ENNM (EfficientNet)	97.8	94.8	96.7	95.74
ENNM (Combined)	98.5	96.4	98	97.2

Table 1 presents a comparative analysis of three proposed models—ENNM utilizing SqueezeNet, ENNM leveraging EfficientNet, and a combined ENNM approach. Accuracy, precision, recall, and F1 score metrics are used to evaluate the effectiveness of every model. The ENNM (SqueezeNet) model demonstrates high accuracy at 98.11%, with precision and recall scores of 95.2% and 97.5%, respectively, yielding an F1 score of 96.33%. Similarly, the ENNM (EfficientNet) model achieves notable results, with an accuracy of 97.8%, precision of 94.8%, recall of 96.7%, and F1 score of 95.74%. Notably, the combined ENNM model outperforms both individual models, boasting an accuracy of 98.5%, precision of 96.4%, recall of 98%, and F1 score of 97.2%. The superior performance of the combined ENNM model suggests the efficacy of leveraging multiple neural network architectures, likely benefiting from diverse feature extraction capabilities. While the ENNM (SqueezeNet) and ENNM (EfficientNet) models exhibit competitive performance, the combined ENNM model excels in all metrics, indicating its potential for enhanced classification accuracy and robustness. Overall, the results highlight the effectiveness of combining different neural network architectures within the ENNM framework, emphasizing the importance of leveraging diverse methodologies to achieve superior performance in ML tasks.

5 Conclusion

In conclusion, our study presents a novel approach for predicting and classifying crop production using an ENNM that integrates the SqueezeNet and Efficient Net architectures. The effectiveness of our ENNM framework, achieving an impressive accuracy rate of 98.5%. By leveraging the complementary strengths of Squeeze Net's lightweight design and Efficient Net's superior performance, our approach offers a robust solution for agricultural forecasting tasks. The integration of advanced ML techniques holds significant promise for revolutionizing agricultural decision-making and empowering precision farming initiatives.

6 Declarations

6.1 Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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