A SURVEY ON TAPIOCA YIELD PREDICTION AND DISEASES IDENTIFICATION USING NEURAL NETWORKS

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Abstract

Developing efficient and reliable methodologies for assessing and forecasting the root yield of Cassava/Tapicoca might minimise the time and effort required to phenotype complex variables related to productivity and abiotic stress. To find phenotypic factors highly associated with Fresh Root Yield (FRY) and to construct a model to predict genotype performance under water shortage conditions. One of the most challenging problems confronting agricultural specialists throughout the globe in recent years has been automating the diagnosis of numerous plant diseases. In this review, to analyze the tapicoca yield prediction and disease identification was analyzed. Cassava Brown Steak Disease (CBSD), Cassava Green Mite (CGM), Cassava Bacterial Blight (CBB), and Cassava Mosaic Disease (CMD) and health impacts are employed in this investigation for earliest possible detection of the disorders. We collect 26 recent papers for survey in disease detection in cassava plants based on a Neural Network (NN). Neural Networks will automatically learn the characteristics in cassava plant images that indicate the presence of illness.

Keywords: Cassava, Disease Identification, Disease Prediction, Yield Prediction
DOINumber:10.48047/nq.2022.20.22.NQ10180 **NeuroQuantology2022;20(22):1926-1936**

I .INTRODUCTION

Cassava is referred to as Tapioca in Indian English usage [1]. Tapioca is a processed starch product extracted from cassava, a root vegetable that's found throughout South America. It's made by grinding cassava roots to a pulp and filtering out their starch-rich liquid, which is then dried into tapioca flour [2]. The critical food crop cassava is mainly grown for its roots. It is the principal source of carbohydrates in developing countries such as South Africa and Southeast Asia, supplying over 500 million people with a necessary diet. [3-8] Cassava is among the food staples [9-12]. In addition to being used as a culinary item, cassava flesh may also be processed into flour. The peel of a cassava root may be used as animal feed if it is milled into a specific animal feed flour. For photosynthesis to occur, green plants need light (chlorophyll). It indicates that the equator is a fertile location for manufacturing carbs since this area gets the most significant and extended sunshine. Cassava is thus one of the food products that must be evaluated [13-18].

If one researches nutritious foods, Cassava in its many processed forms remains the best option. Vitamins, minerals, phytochemicals, and fibre are found in Cassava or sweet potato (pectin, cellulose, hemicellulose). There are several nutrients in Cassava that are useful to the human body. Therefore, it is deemed vital to do the study on Cassava. Pests and illnesses cannot be isolated from cassava agriculture. Uret (Xylenthropus) and Red Mites are two of the invading pests. Bacterial leaf spot, bacterial wilt (Pseudomonas solanacearum E.F. Smith), brown leaf spot, concentric leaf spot, and weed are all diseases; nevertheless, weed is not a disease. Cassava plant diseases were also detected with the use of AI [19].

The paper details a method for automatic crop identification and growth track. Identifying plant diseases is an essential social service that both human experts and intelligent machines can reliably automate. Automatic disease diagnosis is already routine, thanks to AI-powered tools. Because of advancements in AI technology, we can now make use of automated systems that help us diagnose diseases more quickly and efficiently and reduce the burden of human error [20]. The advancement of artificial intelligence and automation systems is essential for the control and treatment of plant diseases[21-26]

Type of Cassava Disease

Cassava illness is classified into different categories.

1) Bacterial leaf spot. Xanthomonas Manihot or Cassava Bacterial Blight is the cause (CBB). The leaf's angular patches are ubiquitous, and their characteristics ultimately lead to its demise. Cutting or eliminating unhealthy plant portions, planting bacteria-resistant cultivars, crop rotation, and garden cleanliness are plant controls.

2) The insect pest causes Cassava green mites (CGM). The weight of the leaves might decrease by as much as 50 per cent, and the yield of the tubers could decrease by as much as 80 per cent if this disease spreads. The symptoms may be reduced by repeatedly scrubbing the leaves with hot water. Details about the plant's leaves, stalks, and roots might be shown. When this happens, the plant's foundations, including its stems and tubers, decay. Crop rotation, removing and eliminating severely infected plants, and planting bacteria-resistant plant varieties like Adira 1, Adira 2, and Muara are all effective plant management methods.

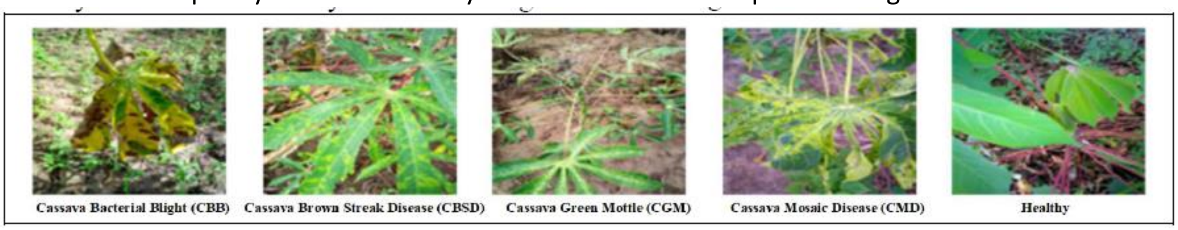

Fig. 1. Sample images from each of the 4 Diseases and Healthy Leaf

3) One of the leaf areas has turned brown—Cassava brown line disease (CBSD). Leaf symptoms include tiny round holes, dark leaf patches, dryness, and dead tissue. Leaf fungus is responsible for this disease. Increased spacing between resistant varieties, the removal of diseased leaves, and periodic garden cleaning all contribute to achieving this goal.

4) The Cassava common mosaic virus causes Cassava mosaic disease (CMD). Diseased leaves have a golden mosaic pattern, or their veins stand out more clearly (vein banding). Virus infections generate localised chlorotic or necrotic spots but no other symptoms. Additional characteristics include mottling, distorted and bent leaflets, and decreased leaf and plant size[4].

II BACKGROUND STUDY

2.1 Survey on Tapioca Yield prediction

Dos Santos Silva et al. (2019) [5] These authors hypothesised that physiological measures would serve as valuable indicators of drought tolerance in Cassava; however, when examined separately, these parameters were not adequate to predict new root production. Instead, more precise prediction models need agronomic data gathered in the latter stages of experiment evaluation. Research indicates that shoot production, root density, leaf count, and leaf area index are most important in rainfed environments. However, the first two characteristics were of more significant relative value in well-watered areas. Cassava root yield could be predicted with the most remarkable accuracy using the ELM, PLS, and GLMSS models, among the features and prediction models considered.

J, V. K. G. Kalaiselvi et al. (2021) [9] Expressions Suggested by the Author Methods for analysing the data included data deduplication, normalisation, and classification, as well as exploratory analysis, model building, and evaluation. As the last step, these authors use a machine learning approach to make yield predictions, with mixed results. These authors research ultimately yields the following data for foreseeing harvests. To better guide their choices, farmers will have access to data on crops that have never been farmed before and a complete catalogue of all available crops. These authors strategy also accounts for collecting past data, which gives the farmer insight into factors like market demand and crop expenses. With the correct input of climate data, user-friendly website might be used to predict crop production for any crop anywhere in the world.

Considering numerous factors, Vitor et al. (2019) [25] presented a method to lower the expense of phenotyping cassava for tolerance to water shortages. 1) At 4 MAP, much less biomass (shoots and roots) was produced than at 12 MAP. These authors meant phenotyping could be done in much less time. Tolerance phenotyping for water scarcity at 4 MAP would allow for evaluation cycles of at least three years in the exact location, allowing for more efficient use of land and faster screening of germplasm and segregant populations. 3) Since field trials only take four months to set up and execute, the costs of doing so are drastically lowered. 4) The time it takes to breed Cassava, a plant that can withstand periods of drought, would be reduced. 5) Selection for tolerance of water limitations happening at the adaptation location would improve the probability of adopting new cassava varieties

Table 2.1 comparitive analysis of Tapioca Yield prediction

Paper no	Author	Methodology	Dataset	Limitation

5	Dos Santos Silva et al (2019)	CART (classification and regression trees), ANN (artificial neural network), SVM (support vector machines), ELM (extreme learning machine), GLMSS (generalised linear model with stepwise feature selection), and partial least squares (PLS).	Nine of the 14 features analysed for the well-watered treatment were biological data.	Cassava's drought tolerance was mainly reflected in physiological markers, although these alone were insufficient to predict fresh root yield.
9	J, V. K. G. Kalaiselvi et al (2021)	Random Forest Algorithm	crop information, local weather forecasts, and geographical details	information about the crop, the climate of a particular region, and the area
18	S. Vashisht et al. (2022)	Kalman Filter Algorithm Extreme Learning Machine	This monitoring data was regularly augmented with other information, such as soil test results and publicly accessible worldwide databases that may be used to anticipate crop growth, rainfall, soil fertility, and other yield-maximising techniques.	It takes a long time to gather yield data for analysis.
25	Vitor et al. (2019)	Linear regression with stepwise selection (LRSS) Linear regression with backward selection (LRBS)	Information on the physiological and agronomic characteristics of the plants was gathered at 4 MAP and two different watering levels.	The suggested technique lacks high-performance phenotyping methods.

2.2 Survey on Tapicoca Disease prediction

A.Maryum et al. (2021) [2] These authors used a unique deep learning architecture, EfficientNet, to swiftly and effectively categorise cassava leaf disease photos. Cassava was a popular food crop not just because it was inexpensive but also because it could tolerate severe weather conditions. However, it was very susceptible to a wide range of diseases brought on by various viruses and bacteria. Some of these illnesses were prevalent and had deadly consequences if not recognised and treated promptly. A dataset from the Kaggle competition was employed for a cassava leaf disease classification with around 21K photos. For classification, these scientists used EfficientNet model B4 using the original image resolution of 512x512 to lessen the amount of data loss and to better capture fine-grained patterns in the images. U-Net, a semantic segmentation model, was also used by scientists to extract leaf shapes from the images, contributing to improved performance. These Authors performed adequately, with an accuracy of 81.48 on the whole dataset and 89.09% on the segmented dataset.

Choi, C., and Hsiao, T.-C., 2021, [3] Authors have created a ResNet-based image classification model for crop disease detection. The network was improved and optimised by examining the results of image categorisation. The crop disease classification model was enhanced for generalisation and actual use.

Thai, H.-T., et al. (2021) [7] These Authors constructed a system to detect diseased leaves, with promising outcomes. The author then quantifies the model to minimise its size by a factor of three, deploys it, and wants to link this gadget to a drone so that the camera can immediately examine and detect contaminated leaves. This effort will aid in the early detection of unhealthy plants, safeguarding their output before irreversible harm occurs and making a modest contribution to the development of intelligent agriculture.

J. F. Tusubira et al. (2020) [10] Using machine learning and image analysis approaches. Whitefly counts on cassava leaves were more accessible thanks to the author's proposed automated process. According to the findings, both the Haar Cascade classifier and the Faster-RCNN can produce accurate results in this scenario. consequently, using machine learning to count whiteflies was a viable strategy. With an F1 score of 0.89, the Faster-RCNN model scored remarkably well, demonstrating that convolutional neural networks could learn whitefly characteristics quite effectively. Whitefly counts on more leaf samples than can be analysed manually using the current method might be significantly increased if these models were disseminated for in-field use on portable devices like cell phones. While the models may not be able to count whiteflies as precisely as a human expert, their high Precision suggests that they may be applied as a semi-automated solution using both machine and human, with the human expert focusing on counting false negatives (whiteflies left out by the models).

J. Srivastava and Manick (2022 [11] proposed an overfitting model. Overfitting is a mathematical mistake when several data points are closely related to several characteristics. Consequently, this model was also highly beneficial for referencing other datasets with a significant class imbalance.

Table 2.2 comparitive analysis of Tapioca disease prediction

Paper no	Author	Methodology	Dataset	Limitation	Accuracy
2	A. Maryum et al. (2021)	EfficientNet model B4	The dataset was obtained via a Kaggle competition and comprised 21,367 annotated pictures with 512x512x3 resolution acquired during a routine survey.	dataset was imbalanced	89.09%

3	C. Choi and T. -C. Hsiao (2021)	categorisation of images using the Residual network ResNet	The dataset contains 21,397 annotated photos of four distinct cassava leaf diseases.	Learning might be inefficient if the network is too shallow.	
7	H.-T. Thai et al.(2021)	Instead of a convolution neural network, a vision transformer (ViT) was used	The 21397 images in this collection depict cassava leaves in various health states, including CBB, CBSD, CGM, CMD, and healthy.	Infectious illness on leaves cannot be evaluated and detected automatically by the model.	90.3%
10	J. F. Tusubira et al (2020)	Haar Cascade and Deep Learning techniques.	a series of 7500 photos of whiteflies	The models may not achieve human-level Precision.	89%
11	Manick and J. Srivastava (2022)	Convolutional Neural Network	Cassava Bacterial Blight (CBB) (1087 pictures), Cassava Brown Steak Disease (CBSD) (2189 photographs), Cassava Green Mite (CGM) (2386 images), Cassava Mosaic Disease (CMD) (13158 images), and Healthy Cassava are shown in this collection (2577 images).	Overfitting was seen in the model.	77%

2.3 Survey on Tapicoca Disease identification

A.A. John (2022) [1] Deep Learning was used to develop a detection model to identify plant illnesses by analysing photos of cassava plants. It allowed the author to provide a solution to the challenges encountered by farmers farming Cassava. These authors examined the treatment of the class imbalance issue and offers a strategy for developing a CNN identification model that may be used in practice. These authors model architecture learnt 12,492,805 parameters and, with an AUC score of 96%, successfully identified the plant illnesses contained in the photos.

H. Zhang et al. (2021) [8] These authors propose a self-supervised disease detection model for Cassava. By using two control trials, SimCLR's efficacy was examined correctly. 10% of the data sets were utilised to validate the training set during model training, while the remaining data sets were divided into several training dataset proposals. The findings indicate a 50-20 (50 % labelled training sets and 20 % unlabeled training sets) unsupervised/supervised learning ratio (50 % labelled training sets and 20 % unlabeled training sets), SimCLR may retain high accuracy of illness identification while reducing the number of tags.

S. Mathulaprangsan and K. Lanthong (2021) [17] The author looked at many CNN-based algorithms for disease classification in cassava leaves. It was determined how well each model classified data, such as CNN (manual setup), VGGs ResNet, DenseNet, and Inception. The top-performing classifier was then subjected to several enhancement procedures, including a horizontal flip, a vertical flip, a rotation, a brightness change, and a zoom adjustment. According to the study results, DenseNet121's classification score of 80.52% was the highest without any augmentation. Its classification accuracy increased to 94.32% when the brightness adjustment improvement was implemented.

V. Y, N. Billakanti et al. (2022) [24] By studying cassava leaves, these authors tackled the issue of recognising and categorising plant diseases. The primary purpose was to develop a classification system for cassava leaf diseases. These authors research suggested using the EfficientNet-B0 model [18], a cutting-edge technique. It was a technique for equally scaling all depth/width/resolution dimensions using a compound coefficient. These authors surpasses previous studies on the early identification and categorisation of cassava leaf diseases. The existing might aid farmers and the agriculture sector and conclude that the suggested model delivers satisfactory performance based on experimental findings. The entire system accuracy achieved 92.6%.

Table 2.3 comparitive analysis of Tapioca disease identification

Paper no	Author	Methodology	Dataset	Limitation	Accuracy
1	A.A.John (2022)	Convolutional Neural Network (CNN)	It includes 21397 photos of leaves from five distinct classes, four directories of four distinct illnesses, and one of the healthy leaves.	The model cannot accept real-time video input, and the original dataset was unbalanced	96%.
8	H. Zhang et al. (2021)	Image categorisation using self-supervised learning	There were 21397 cassava photos in the collection.	The efficacy of unlabeled training sets decreases considerably.	91.59%
17	S. Mathulaprangsan and K. Lanthong (2021)	CNN model including VGGs, Res Net, Dense Net	Cassava bacterial blight (CBB), Cassava brown streak disease (CBSD), Cassava green mite (CGM), and cassava mosaic disease are among the four illnesses in that dataset (CMD). More than 22,031 cassava leaf photos are included in the collection.	Only photos from the training set are used.	94.32%
24	V. Y, N. Billakanti et	EfficientNet-B0	It consists of a total of 21,367 photos, which are separated	Overfitting may occur when	94.70%.

	al (2022)		into five classes: Cassava Bacterial Blight (CBB) (1,087 photographs), Cassava Brown Streak Disease (CBSD) (2,189 images), Cassava Mosaic Disease (CMD) (13,158 images), Cassava Green Mottle (CGM) (2,367 images), and Healthy Cassava (2,577 images)	there are a significant number of epochs.	

III DISCUSSION

The primary objective of this study was to determine which physiological and agronomic factors are most closely correlated with root output among different cassava genotypes. Shoot yield, and NRP (roots per plant) were the most crucial agronomic characteristics. Prediction models for dry environments should contain the leaf area index and other factors that represent the genotypes' aptitude for biomass production, such as shoot yield, number of leaves, and the total number of roots. Water and nutrient efficiency in the field may be predicted using characteristics like shooting biomass, root diameter, and branching density, making them useful for the early growth stage selection of cassava genotypes.

Three different machine learning methods were tested, with the SVM model demonstrating the highest level of predictive accuracy across all six disease categories. When trained on the original dataset, the SVM model demonstrated the highest accuracy (96%) for identifying instances of cassava mosaic disease (CMD) and red mite damage (RMD) and the highest accuracy for identifying instances of healthy and brown leaf spot (BLS) when training on the leaflet dataset. For the leaflet dataset, the Inception v3 model had the highest accuracy for detecting Cassava brown streak disease (CBSD) and the second-highest accuracy (95%) for detecting green mite damage (GMD). The low grade for this sickness is due to the wide range of presentation within the same class: at first, symptoms emerge as translucent, water-soaked dots; subsequently, these spots morph into dark green spots; finally, the spots grow and unite to create vast brown patches. Other infected groups, however, have scored higher than 83% due to subtle differences in the lesional patterns even within the same category.

IV. CONCLUSION

This research demonstrated how data mining methods might be used to estimate crop production based on climatic input characteristics. The built-in website is simple to use, and we used transfer learning from the convolutional neural network to examine the accuracy of picture identification in different conditions and locations. The latest version of Inception is an effective method for automating the detection of cassava diseases with a high degree of accuracy. This method allows to train a model on a desktop and then deploy it to a mobile device, skipping the time-consuming and labour-intensive process of extracting features from pictures. Transfer learning may also use traditional machine learning methods by retraining the vectors produced by the learnt model with new class data. Three different machine learning methods were tested, with the SVM model demonstrating the highest level of predictive accuracy across all six disease categories.

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