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AI-BASED SOLUTIONS IN AGRICULTURE: FERTILIZER PREDICTION AND TOMATO DISEASE DETECTION USING MACHINE LEARNING AND COMPUTER VISION

Abstract

This research is aimed at using artificial intelligence to improve agricultural practice in Kazakhstan. It focuses on tomato leaf disease detection and fertilizer optimization. Deep learning models – including GoogleNet (InceptionV3), VGG16, ResNet50, MobileNetV2, and a custom Convolutional Neural Network (CNN)–were evaluated for disease detection. GoogleNet had the highest accuracy of 99.72%, which shows its capability to detect tomato leaf diseases. For the optimization of the fertilizer, different machine learning-based models, namely Decision Trees, K-Nearest Neighbors, CNN, Gradient Boosting Decision Tree, LogitBoost were assessed using various PCA features. The CNN model that used six PCA features achieved the best accuracy at 97.58%. This shows how good features can help in prediction. The results show using AI technologies can significantly increase the agricultural productivity and sustainability of Kazakhstan through precise detection of diseases and optimized use of resources. In the future studies, models should be deployed to the real-time system of agriculture and also should be expanded to more crops and conditions.

Keywords: optimization, computer vision, machine learning, deep learning, convolutional neural networks, agriculture, artificial intelligence, plant disease detection, fertilizer optimization, predictive modeling.

Introduction

Kazakhstan is undergoing transformation in agriculture which is an important element of the economy through technology. Greenhouse automation and precision agriculture, amongst these will enhance productivity, sustainability and resource efficiency. It is essential for greenhouse operators to conduct both plant and water diagnosis for better returns and low losses.

Kazakhstan's agriculture is a top-tier industry that could benefit from AI-based solutions tremendously. For example, the Turkestan region provided 34% of the country's tomato production in 2021 thanks to the ideal combination of warmth, nutrients in the soil and the infrastructure for irrigation. Nonetheless, faced with crop diseases and low resource efficiency, the region–and the country in general–faces problems. Due to those problems, people tried a lot of methods to manage the crops.

This study centers on the developing solution namely fertilizer prediction and tomato disease detection in agriculture using AI along with machine learning and computer vision. The objective of the research is to make use of a dataset, having N,P, and K in the soil, temperature, humidity, pH, and rainfall. Analyzing these factors can help in AI's prediction of the exact dosage of fertilizers to utilize for plants while preventing environmental hazards.

In addition, the research looks at how to detect tomato diseases, which influence tomato yield. The project looks at 10 types of diseases of tomatoes like yellow leaf curl virus and other diseases along with healthy plants. This study compares various models using CNN (Convolution Neural Networks) with the most popular option being VGG16, ResNet50, MobileNetV2, and EfficientNetB0 to find the most efficient architecture for disease classification.

Kazakhstan has launched the greenhouse industry. In 2021, more than 2500 hectares of greenhouses were registered, including 300 hectares of high-tech complexes. But present-day greenhouse systems are labor-intensive for monitoring and intervention. AI tools like fertilizer prediction and automated disease diagnosis can greatly boost greenhouse automation. As a result, this allows for timely intervention and reduction of labor work.

The current study presents AI-powered insights for the management of resources and plant health with a view to furthering the greenhouse automation system development. Solutions which will best address problems in agriculture on one hand and solutions which will assist in sustainable agriculture in Kazakhstan on the other hand are proposed.

Machine learning and deep learning methods have made great strides in detecting and classifying plant diseases, particularly tomato plant diseases. Different methods have been explored by various researchers to obtain a disease detection system effectiveness and capability.

An innovative approach employing the Random Forest algorithm was explored by O. Rama Devi et al. fertilizer prediction is 99.27% based on the environment, soil and plant conditions. The study revealed that Random Forest outperforms the K-Nearest Neighbors model (75%), Decision trees (83%) and Support Vector Regression (88%) among other models. Even though the outcomes of the study were reliable but depending on a specific dataset from Kaggle will require it to be more generalized for data [1]. S. Vaishnavi et.al., in their dependency analysis of soil and environmental factors leading to fertilizer recommendations considered nitrogen, phosphorus, potassium, humidity, and rain and more. A comparison of machine learning algorithms like SVM, Random Forest, Decision Tree and Naïve. Their SVM achieved the highest accuracy of 97% [2].

Md Shahid Ali et al. performed an optimization with the AODE algorithm, which combined agriculture datasets that led to crop yield predictions and customized fertilizer recommendations. The objective of Precision Agriculture is to improve the different resource allocation and crop management strategies. According to the report, the level of accuracy of the model is 76.36%. The study gave us new knowledge about using machine learning in farms. But it also used certain datasets and therefore has limited generalization to other crops and farming conditions [3].

Recently, deep learning techniques have made the work more accurate and efficient. A deep learning model was proposed by Mohanty et al. using AlexNet and GoogleNet architectures. The GoogleNet attained accuracy of 99.35%. Although it was quick to classify, the model took a long time to train [4]. In a similar way, Sladojevic et al, used a Convolutional Neural Network (CNN), obtaining a classification accuracy of 96.3%, although fine-tuning of the model was needed [5].

Brahimi et al, achieved a significant 99.18% accuracy through CNN-based architectures. Even though CNN's ability to extract features automatically was efficient, it still had a computational cost [6]. Fuentes et al, used Faster R-CNN with VGG-16 for object detection techniques to improve accuracy and reduce false positives during training [7].

Durmus et al, assessed SqueezeNet and AlexNet in a lightweight model, which found AlexNet giving a better accuracy rate of 95.65%. SqueezeNet was computationally efficient but worked poorly with small batch sizes. Also, Rangarajan et al, used a pretrained deep learning model and achieved 97.49% accuracy with AlexNet with minimum execution time [8].

Recent studies have also focused on enhancement with optimization and augmentation. Zhang et al, explored using ResNet with stochastic gradient descent (SGD), and his achieved accuracy was 97.28%. They focused on computational efficiency through fine-tuning [9]. At the same time, Jiang et al, established the INAR-SSD model that achieves high real-time accuracy but less explored algorithm applications [10].

To overcome the issues with overfitting, Adhikari et al, used data augmentation in their CNN-based model and achieved an accuracy of 89% overall. Results showed that transfer learning can increase the classification results [11].

To sum up, the deep learning models having CNN architecture, namely VGGNet, ResNet, and AlexNet, are among the most noteworthy methods for tomato disease detection with accuracies over 99%. Yet computational complexity, training time, and real-time optimization are all critical issues. In the future, studies should involve lightweight models, advanced feature extraction, and transfer learning for high performance in large-scale agriculture.

Devi Priya and others invented ENSEMBLED CROPIFY, a scheme that recommends the crop, gives fertilizer suggestions, and detects leaf diseases. This system employs various machine learning models for crop recommendation, achieving impressive accuracies, as detailed in Table 9: Random Forest (99.67%), Naive Bayes (99.45%), and SVM (97.36%). For leaf disease classification, the system uses ResNet architecture. This combined method ensures exact suggestions and practical insights, resulting in increased agricultural productivity [12].

The problem statement of the research is formulated as follows: it is necessary to evaluate and analyze the performance of various machine learning and deep learning architectures to accurately identify and categorize diseases in tomato plants while also incorporating recommendations for crop selection and fertilizer usage. The study aims to develop and optimize models providing the most accuracy, precision, recall, and F1 score. The study aims to develop a reliable, efficient, and holistic solution for diagnosis of diseases and management of agricultural affairs by comparing different architectures and optimizing their parameters.

Materials and methods

Datasets

Tomato Disease Detection Dataset

In this research, the data set for the detection of tomato diseases contains 14529 images (256 x 256 pixels). These images are categorized into 10 classes based on tomato diseases and healthy leaves. All classes are kept in individual folders to make it easier to classify them. A serious problem associated with this dataset is that some classes have much more images while others are fewer. For example, one class has 4,286 images and another class contains only 299 images. If left uncorrected, this imbalance can cause the model to train poorly and lead to bias.

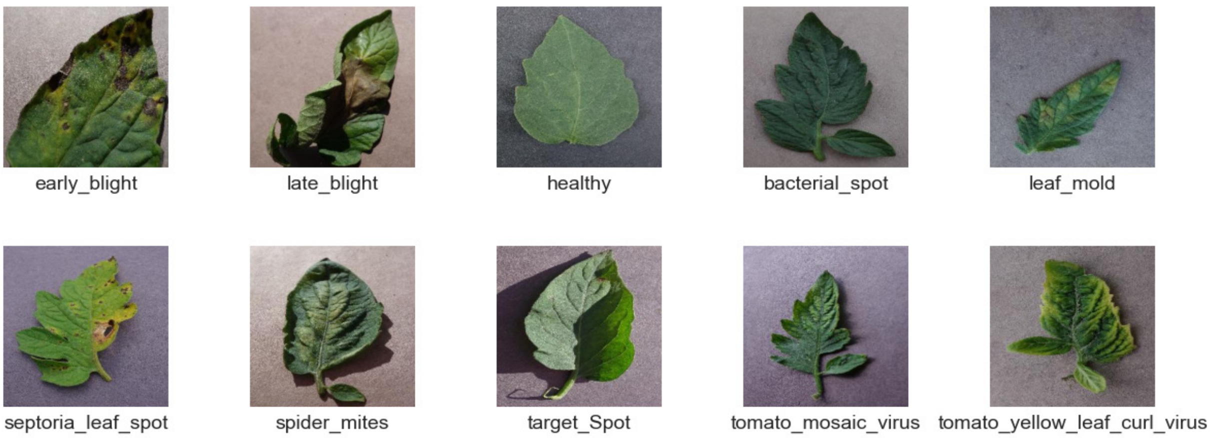

Figure 1 – Sample tomato leaf images from the dataset, showing healthy and diseased classes

The image shows examples of the tomato leaf dataset used for this research. It shows what each class looks like. The images show symptoms of many diseases, as well as healthy leaves, which can be used to develop models for image-based disease detection.

Fertilizer Prediction Dataset

The fertilizer prediction dataset contains seven key features crucial for determining crop health and growth. Their features are nitrogen, phosphorus and potassium content of the soil (kg/ha), along with environmental factors temperature (c), humidity (%), soil pH (0 to 14), and rainfall (mm). Each data point has been labelled with the crop most suitable for given conditions. This dataset is organized and designed for supervised learning tasks such as classification or regression.

The Figure of the table below shows some data of nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, soil pH and rainfall along with the crop.

Crop_recommendation

1	N	P	K	temperature	humidity	ph	rainfall	label
2	90	42	43	20.87974371	82.00274423	6.502985292000001	202.9355362	rice
3	85	58	41	21.77046169	80.31964408	7.038096361	226.6555374	rice
4	60	55	44	23.00445915	82.3207629	7.840207144	263.9642476	rice
5	74	35	40	26.49109635	80.15836264	6.980400905	242.8640342	rice
6	78	42	42	20.13017482	81.60487287	7.628472891	262.7173405	rice
7	69	37	42	23.05804872	83.37011772	7.073453503	251.0549998	rice
8	69	55	38	22.70883798	82.63941394	5.70080568	271.3248604	rice
9	94	53	40	20.27774362	82.89408619	5.718627177999999	241.9741949	rice
10	89	54	38	24.51588066	83.53521629999999	6.685346424	230.4462359	rice
11	68	58	38	23.22397386	83.03322691	6.336253525	221.2091958	rice
12	91	53	40	26.52723513	81.41753846	5.386167788	264.6148697	rice
13	90	46	42	23.97898217	81.45061596	7.50283396	250.0832336	rice
14	78	58	44	26.80079604	80.88684822	5.108681786	284.4364567	rice
15	93	56	36	24.01497622	82.05687182	6.98435366	185.2773389	rice
16	94	50	37	25.66585205	80.66385045	6.94801983	209.5869708	rice
17	60	48	39	24.28209415	80.30025587	7.0422990689999985	231.0863347	rice

Figure 2 – Feature distributions in the fertilizer prediction dataset

Every row is a complete profile that is used to assess what crop would be most suitable under given environmental conditions.

Preprocessing Steps

Tomato Disease Detection Dataset Preprocessing

For each deep learning architecture (GoogleNet, VGG-Net, ResNet, MobileNet, Custom CNN), two models were trained: one with data augmentation and the other without. To overcome the unequal representation in the dataset, the augmented models used sizes of rotating flipping scaling and cropping to increase representation of underrepresented classes. The inclusion of semantic comprehension tasks contributed to a more diverse dataset and helped improve the robustness of the models. We changed the size of all images to 256 × 256 pixels. Similarly, we changed the pixel values from [0, 256] to [0, 1]; to help faster convergence while training.

The training, validation, and test sets of the dataset adopted a stratified sampling approach. There was a proper distribution of classes in the train, validation and test sets. While training, learning rate, batch size, epoch, and other parameters were tuned for optimal performance. To further prevent overfitting in CNN architectures and improve generalization, overfitting dropout, and batch normalization techniques were integrated.

The image shows the different conditions of tomato leaves from the dataset. The states differ based on disease and healthy appearance. The pictures show how producing data was done by using rotating, flipping, scaling, and cropping in the data set. With the help of these manipulations robustness of the models is increased as they are provided with more varied examples of each class. The models learn more robust representations of each class.

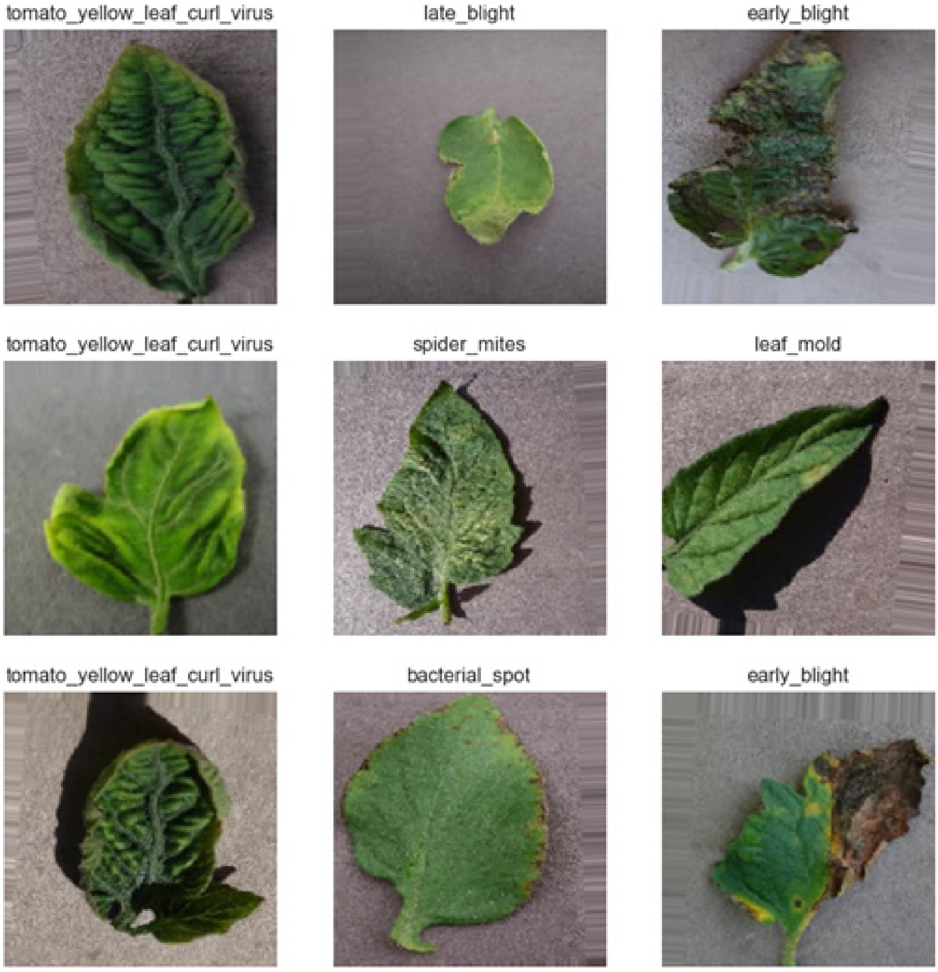

Figure 3 – Examples of Data Augmentation Techniques on Tomato Leaf Images

Fertilizer Prediction Dataset Preprocessing

The fertilizer prediction dataset underwent normalization to scale numerical features uniformly, improving model performance and preventing bias due to differing feature ranges. Principal Component Analysis (PCA) was used to reduce dimensions by retaining the most important features. Many experiments were done with combinations of six, five or four features (out of total seven) to identify best set of features which gives the best result in terms of accuracy, precision, recall and F1-score. We split the dataset into the training, validation, and testing subset to check the robustness of the models.

Evaluation Metrics

All models are evaluated using four metrics which include accuracy, precision, recall, and F1 score. The accuracy is the measure of how many classifiers were correct with answer predictions. Mathematically, the accuracy is defined as the sum of true positives and true negatives divided by total instances. Precision measures the proportion of positive samples accurately predicted from all samples predicted as positive and indicates the model's ability to reject negative samples. Recall, which is also called sensitivity, is the percentage of positives that were predicted out of the total actual positives. It assesses whether the model recognizes all relevant instances. F1-score balances precision and recall by calculating their harmonic mean, allowing for a more complete measure. The metrics for each model on the test dataset were calculated so that comparisons between architectures and machine learning methods are consistent and fair. We used the results to find the best configurations for the tomato disease detection and fertilizer prediction tasks.

$$Accuracy = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Number of Samples}}$$

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$Recall = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Evaluation of Deep Learning Architectures for Tomato Disease Detection

Today, specially designed computer vision architectures help feature extraction, classification, and optimization make the computer vision systems more reliable and robust. This study analysed the connectivity and performance of GoogLeNet, VGG, ResNet, MobileNet, and Custom Convolutional Neural Network Architecture. Each architecture differs in design philosophy, computational complexity, and adaptability, making their evaluation essential for industrial applications.

GoogleNet

GoogleNet employs inception modules that concatenate multiple convolutional filters (1x1, 3x3, 5x5) to capture multi-scale spatial information. Having 22 layers and less parameter in comparison to VGG makes it perform well at reasonable cost. This structure is excellent for relying on high-quality error-free operations without too much hardware. Figure 1 shows GoogleNet's design.

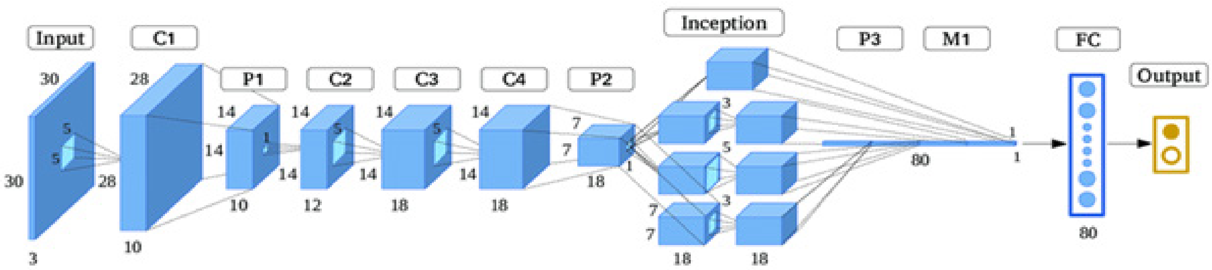

Figure 4 – GoogleNet Architecture

This shows the GoogleNet architecture which has inception modules which can deal with multi-scale spatial information at low parameters. This architecture can perform complex image recognition tasks while using less computational resources, making it useful for environments with low hardware capabilities. The image shows how different convolutional filters are stacked and combined in GoogleNet which allows it to have higher accuracy with less computation.

VGG-Net

VGG uses a series of small (3×3) convolution filters and pooling layers sequentially to construct a deep network having an architecture of 16 or 19 layers. Even though it achieves high accuracy, it needs a lot of computations because it has a high number of parameters. This architecture is useful for feature extraction because it learns features in a hierarchical way. The VGG architecture is shown in Figure 2.

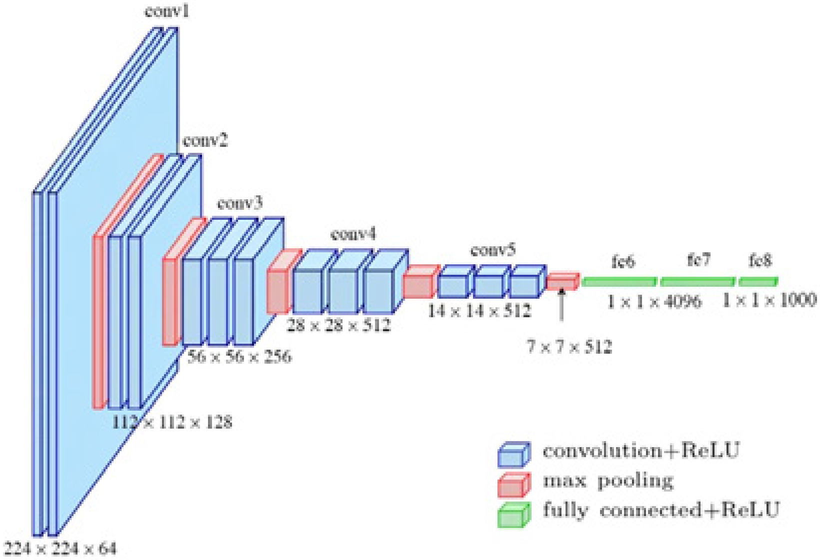

Figure 5 – VGG-Net Architecture

This figure displays the detailed structure of the VGG architecture, characterized by its deep layers of small 3x3 convolutional filters followed by max pooling layers. The image shows that as the more layers are used, the less spatial dimensions are used and more depth is used to extract and learn features. VGG makes use of high numbers of convolutional layers stacked on top of each other to get high accuracy. This accuracy, however, comes at the cost of high computation due to the high number of parameters.

ResNet

ResNet solves the vanishing gradient problem with residual connections that allow gradients to flow more readily through the network. Variants of ResNet-50, ResNet-101, and ResNet-152 allow scalability to deeper networks. ResNet performs excellently in cases where deep models are required, and it trains reliably and accurately. The structure of ResNet is shown in Figure 6

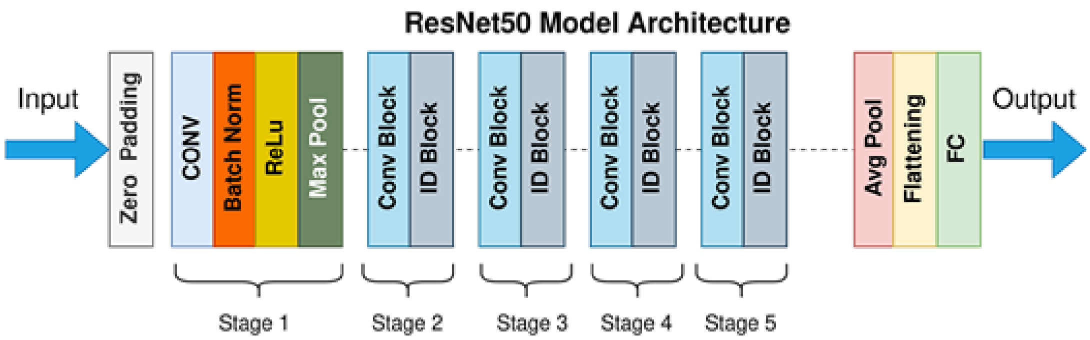

Figure 6 – ResNet Architecture

This diagram shows the architecture of ResNet and how it uses residual connections. These connections serve as transitions between layers, allowing gradients to skip over layers and flow to earlier layers, thus solving the vanishing gradient problem. The sequence of layers that make the core of ResNet include convolutional blocks and identity blocks. It trains the very deep networks. The ResNet architecture is capable of high accuracy, and training, offering high accuracy and training on deep learning on a variety of tasks.

MobileNet

MobileNet uses depthwise separable convolutions that drastically lower the cost but provide a high end performance. This is particularly useful for mobile embedded systems. This allows for deploying a neural network on a device with limited computing power—like a smartphone, IoT, or an embedded device.

MobileNet type lightweight networks can run self-sufficient tasks that require real-time decision making. Examples of use: real-time object detection, image classification, face recognition and edge computing. MobileNet is very powerful as it can compute quickly and take less power for its computation. MobileNet treads the fine path of efficiency that is speed and power.

MobileNet is a widely used architecture because of its simplicity and modularity. The process of applying depthwise separable convolution can be seen as a factorization of the standard convolution. This factorization includes two streamlined operations, depthwise convolution, and pointwise convolution. The former does spatial filtering and the latter combines features across channels.

By using this method the number of trainable parameters and the computing complexity has decreased considerably while still giving comparable performance to conventional architectures.

As we can see in figure 7, MobileNets are made up of depthwise separable convolutions. These operations have a lightweight architecture for efficient processing.

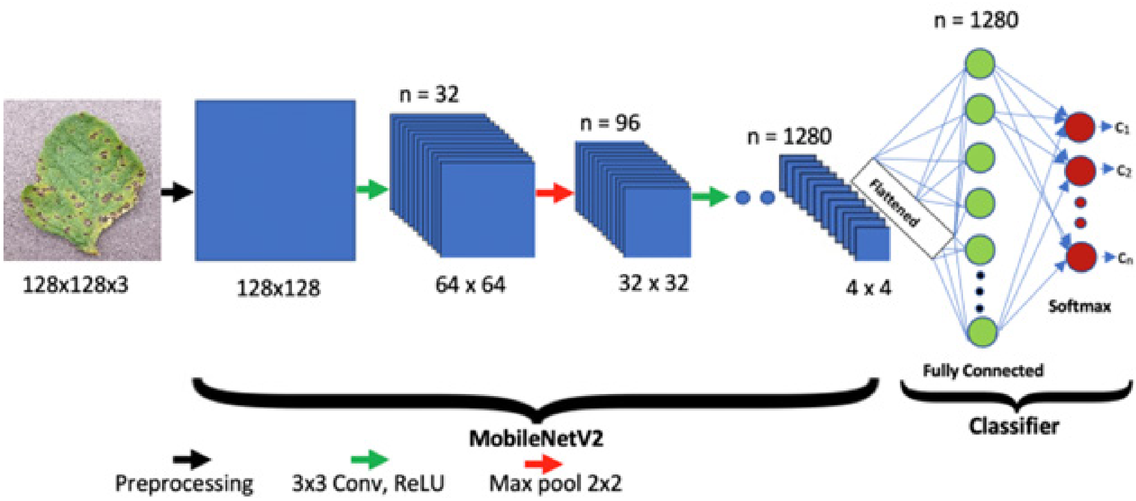

Figure 7 – MobileNet Architecture

MobileNet architecture is shown in this figure which is developed for better efficiency. It shows a use of depthwise separable convolutions which reduces the time complexity significantly while maintain efficiency. The flow starts from preprocessing and passes through various convolutional and pooling layers, finally reaching the full connection layer for classification. MobileNet's blocks have been optimized to make the model work with minimum resources making it a good option for speed and low power usage.

Custom Convolutional Neural Network

For this study, a custom-wise convolutional neural network (CNN) was developed which satisfied the requirements of the study. The design was carefully made to balance the model complexity and computation efficiency while ensuring robust performance and keeping the model light enough. The structure of the network involves four convolutional layers, which are layers that extract features, and is followed by max-pooling layers to reduce overfitting.

The model will make use of 32 filters in the first convoluted layer. The model will leverage this to get patterns and images from the input outlined image. In later layers, the number of filters in each layer gradually increases to 64. The layers learn more complex and abstract features as the layers get deeper. By using max-pooling after every convolution block, high spatial information is retained while the computational cost is reduced.

To enhance generalization and reduce overfitting, we utilize a rescaling layer to preprocess the input images. This layer scales pixel values to the range [0, 1]. normalization helps in numerical stability and speeding up training process. Near the network's conclusion a dense layer having 64 neurons and ReLU activation gets high-level representations. The output layer contains 10 neurons having a softmax activation function. The neural network is therefore suitable for the multi-class classification problem.

The model uses the Adam optimizer and a sparse categorical cross-entropy loss function to optimize its performance and training. The training of the model gets stopped in case the model overfits. In this way, it performs better on unseen data.

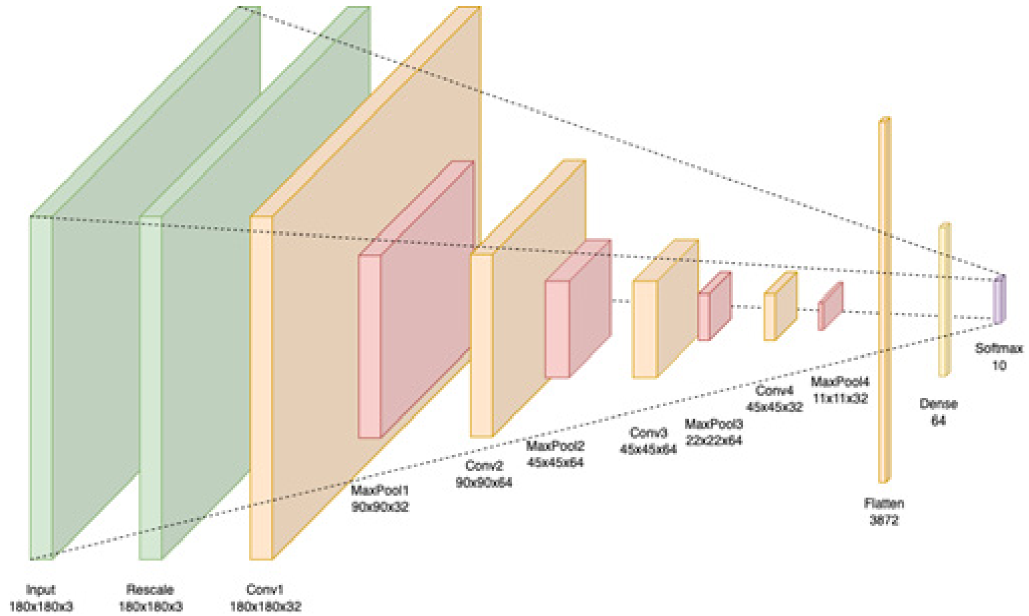

Figure 8 – Architecture of the Custom CNN

Figure 8 shows how the layers of the Custom CNN are arranged. While training, early stopping was employed that halts the training once the model has started to overfit.

This architecture creates a balance between depth and computational cost. Thus, it is very flexible for any industrial application. Such as, defect detection in production lines. It effectively extracts important features without being too complex.

Analysis of Machine Learning Models for Fertilizer Prediction

The fertilizer prediction task was approached using various machine learning techniques, each tailored to analyze the dataset's features and provide accurate predictions. The following sections summarize how we used different models and what they revealed.

K-Nearest Neighbors

K-Nearest Neighbors is a simple, instance-based learning algorithm that classifies a data point based on the classes of its nearest neighbors. KNN identifies the k neighbour points in the feature space and assigns the most common class among the neighbours which is to be assigned to the new point. The algorithm is non-parametric. It makes no assumptions about the data's distribution. It works best when the decision boundary is not well defined. The hyperparameter k is a crucial component that can impact a model's performance. When larger values of k are used, a smoother decision boundary is produces. Conversely, smaller values of k produce more flexible decision boundaries.

In this research, using KNN the crop suitability was predicted by using soil nutrients, temperature, humidity and pH features. The experimental determination of k was made to optimize the model.

Decision Tree

Decision Trees are tree-type classifiers. Here, each internal node is a feature (or attribute), each branch is a decision rule and each leaf node is an outcome (class label). To develop the tree, we continually split the data according to the feature that generates maximum information gain, or reduction in Gini impurity. Trees made from the Decision Tree model are easy to interpret as the tree can be visualized easily and traced accordingly to understand the decision made for any data points.

For our purpose, we applied Decision Trees to predict the type of crops a farmer should grow relative to soil nutrients and environment. The tree classifies the best crop for a given set of conditions by splitting on features like nitrogen levels or rainfall.

Convolutional Neural Network

While CNNs generally function on image data, this tabular dataset was experimented with by converting its features to be arranged in a matrix. By employing such a method, CNNs managed to benefit from their structural arrangement for gathering features. Even though CNNs applied a new application, tabular-specific models still did better.

K-Means Clustering

The K-means algorithm was used as an unsupervised learning technique to find hidden patterns. K-Means helped in discovering the potential relationship between features and distribution of the cluster by clustering the similar data points together. Nonetheless, it needed precise tuning of number of clusters (k) to fit with the structure of the data.

Gradient Boosted Decision Trees

Gradient Boosted Decision Trees make a strong predictive model by combining a number of weak decision tree learners. There was a high performance of GBDT after minimizing errors and optimizing weights on fertilizer dataset. It handles feature interactions and imbalanced data really well and therefore, the best out of all other models tested.

Gradient Descent Applied to Logistic Regression

Logistic regression model basically computes the logits that are the computed value the value is obtained by multiplying the input features with weights and adding bias. The softmax function translates these logits into probabilities in deep learning algorithms. The softmax function takes the raw scores and normalize those to obtain probabilities of each class. The softmax function is used for multi-class classification. For multi-class classification, the softmax function is defined as:

$$P(y = k \mid x) = \frac{\exp(logit_k)}{\sum_{k=1}^{K} \exp(logit_k)}$$

where $logit_k$ is the raw score for class k, and $P(y = k \mid x)$ is the predicted probability for class k.

Gradient descent works by adjusting the model's parameters repeatedly to minimize the difference between predicted probabilities and true labels. We determine the error by subtracting the true label (one-hot encoded) from the predicted probabilities. After this, we compute the gradients of the weights and bias by evaluating the cost function cross entropy loss's derivatives. The cost function helps measure how accurate our model is. The gradients show how much each parameter contributes to the error, so to reduce the error the change in each parameter needs to occur in the negative gradient direction.

At each epoch of the gradient descent process, the weights and bias are updated using the calculated gradients. The update rule for the weights and bias is as follows:

$$weights = weights - \eta \cdot \nabla_{weights}$$
$$bias = bias - \eta \cdot \nabla_{bias}$$

where learning rate is represented by , which is a hyperparameter that governs the step size of the learning algorithm. The process is done for a fixed number of epochs until there is no improvement in the accuracy of the model.

Results

In this research, performance of various deep learning models for detecting tomato leaf diseases was evaluated. The evaluated models are GoogleNet (Inception V3), VGG16, ResNet50, MobileNetV2, and Custom CNN. Each model was trained using a specific learning rate. Subsequently, the metrics were calculated on their performance. These metrics include accuracy, precision, recall and F1 score.

The results are provided in the Table 1.

Table 1 – Deep Learning Model Metrics for Tomato Leaf Disease

Model	Learning Rate	Accuracy	Precision	Recall	F1 Score
GoogleNet(InceptionV3)	0.00001	0.9972	0.9972	0.9972	0.9972
VGG16	0.001	0.9649	0.9654	0.9649	0.9650
ResNet50	0.001	0.9833	0.9833	0.9833	0.9833
MobileNetV2	0.001	0.9271	0.9269	0.9271	0.9263
Custom CNN	0.001	0.9588	0.9589	0.9588	0.9586

The results show that GoogleNet (InceptionV3) achieved the highest accuracy at 99.72% and ResNet50 at 98.33% The Custom CNN, as well as VGG16, performed well with accuracies of 95.88% and 96.49% after fine-tuning the model. To me MobileNetV2 had the least accuracy out of these models. It is 92.71%. Results suggest a deeper architecture such as GoogleNet or ResNet50 may work better for tomato leaf disease detection tasks.

Using these effective models in farming could help find and manage tomato leaf diseases quicker. This could improve growing production and lower losses. Future research may focus on implementing these models in real-time systems and use in precision farming.

I also looked at how machine learning models can help use fertilizers better. I also used PCA to reduce feature dimensions. Models like Decision Tree (DT), K Nearest Neighbors (KNN), Convolutional Neural Network (CNN), Gradient Boosting Decision Tree (GBDT) and LogitBoost(Logistic Regression with Gradient Descent) were trained with different numbers of PCA features. Table 2 shows how well they performed.

Table 2 – Model Performance with PCA Features for Fertilizer Optimization

Model	PCA features	Accuracy	Precision	Recall	F1 Score
DT	3	0.6833	0.6920	0.6892	0.6826
DT	4	0.8303	0.8358	0.8341	0.8319
DT	5	0.8394	0.8415	0.8379	0.8377
DT	6	0.8833	0.8902	0.8888	0.8863
KNN	3	0.7470	0.7476	0.7470	0.7429
KNN	4	0.8848	0.8924	0.8848	0.8842
KNN	5	0.9273	0.9340	0.9273	0.9266
KNN	6	0.9636	0.9670	0.9636	0.9631
CNN	3	0.7470	0.7556	0.7470	0.7478
CNN	4	0.8864	0.8873	0.8864	0.8853

Continuation of the Table 2

Model	PCA features	Accuracy	Precision	Recall	F1 Score
CNN	5	0.9333	0.9353	0.9333	0.9332
CNN	6	0.9758	0.9765	0.9758	0.9758
GBDT	4	0.8076	0.8242	0.8076	0.8046
GBDT	5	0.8500	0.8580	0.8500	0.8493
GBDT	6	0.8803	0.8852	0.8803	0.8789
GBDT	7	0.9379	0.9405	0.9379	0.9384
LogitBoost	5	0.7985	0.8174	0.7985	0.7838
LogitBoost	6	0.8803	0.8852	0.8803	0.8789
LogitBoost	7	0.9015	0.9090	0.9015	0.8995

Fertilizer Optimization, model performance generally improved with the increase in number of PCA features. The accuracy of Decision Tree model improved from 68.33% to 88.33% with the three PCA features and the six PCA features respectively. Likewise, as the PCA features increased from three to six the accuracy of K-Nearest Neighbors model increased from 74.70% to 96.36%. The Convolutional Neural Network achieved an accuracy of 97.58% with six PCA features. The performance of Gradient Boosting Decision Trees and LogitBoost also improved as more PCA features were used.

The findings suggest that using the best amount of PCA features can greatly improve the prediction performance of many machine learning models in fertilizer optimization. But the number of features should be balanced to avoid overfitting. Overfitting is especially true in high variance models.

In summary, using deep learning for detecting tomato leaf disease and using the PCA technique with a machine learning model for fertilizer optimization will be useful for precision agriculture in Kazakhstan. By using these technologies experts say more efficient utilization of resources, timely disease control, and ultimately increased crop yield which may boost the economy of the area.

Discussion

The integration of AI-driven solutions in agriculture presents significant opportunities for enhancing productivity and sustainability, particularly in regions like Kazakhstan. This research looked at how well different deep learning models could detect tomato leaf diseases and machine learning models that used Principal Component Analysis (PCA) features could optimize fertilizers.

GoogleNet (InceptionV3) and ResNet50 models were found to be among the best-performing methods in tomato leaf disease detection with the accuracy of 99.72% and 98.33%. The previous studies that show how deep convolutional neural networks are effective in plant disease identification have found similar results. The excellent precision and recall values further demonstrate the robustness of these models in classifying tomato leaf diseases accurately.

To improve fertilizer, using the right number of PCA features helped make a good prediction of machine learning models. The Convolutional Neural Network attained an accuracy score of 97.58% with six PCA features. This indicates that using fewer but relevant features help improve the outcome of the task. This method conforms with research that highlights the importance of feature tuning to improve crop yield prediction models.

Conclusion

This study shows how AI solutions can change farming in Kazakhstan to become more precise. GoogleNet(InceptionV3) and ResNet50 have proved to be 99.72% and 98.33% accurate, respectively, in the assessment of tomato leaves diseases by using deep learning models. Such high precision allows early disease detection, which allows for interventions that will significantly decrease crop damage and improve quality.

Using PCA features has improved the performance of machine learning models for fertilizer optimization even more than basic data features do. The Convolutional Neural Network had an accuracy of 97.58% with six PCA features. Thus, dimensionality reduction can enhance model's efficacy significantly.

It helps to apply fertilizer correctly, thereby facilitating sustainable farming and reducing environmental impacts with limited resources.

Using these AI technology trend is align with world trend in smart agriculture data-driven decisions sustainable crop management. With such models doing well in Kazakhstan's agricultural landscape, they promise better productivity besides making Kazakhstan a leader in innovative sorghum farming solutions.

In the future, models should be deployed for the practical use in real-life agricultural sites, which can be studied in varying environments and diverse types of crops. Moreover, making dataset larger so it covers more diseases and other crops will increase the strength and universality of the models. Working together with farming professionals who live in Kazakhstan will help make sure that the AI solutions are exactly what the country needs.

To sum up, ai will be important in enhancing food and economic security in Kazakhstan if used in agriculture. Agriculture industry without new and advanced technology cannot move forward. New technology adoption is a must. Only with new technology will agriculture more efficient and productive to meet the growing needs of society.

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АУЫЛ ШАРУАШЫЛЫҒЫНДАҒЫ ЖАСАНДЫ ИНТЕЛЛЕКТ НЕГІЗІНДЕГІ ШЕШІМДЕР: МАШИНАЛЫҚ ОҚЫТУ ЖӘНЕ КОМПЬЮТЕРЛІК КӨРУ АРҚЫЛЫ ТЫҢАЙТҚЫШТАРДЫ БОЛЖАУ ЖӘНЕ ҚЫЗАНАҚ АУРУЛАРЫН АНЫҚТАУ

Аңдатпа

Бұл зерттеу Қазақстанда ауыл шаруашылығын жетілдіру мақсатында жасанды интеллекттің қолданылуын зерттейді. Негізгі назар екі бағытқа аударылды: қызанақ жапырақтарының ауруларын анықтау және тыңайтқыштарды оңтайландыру. Ауруларды анықтау үшін GoogleNet (InceptionV3), VGG16, ResNet50, MobileNetV2 және арнайы конволюциялық нейрондық желілер (CNN) сияқты терең оқыту модельдері бағаланды. GoogleNet моделі 99,72% дәлдікпен ең жоғары нәтижеге қол жеткізіп, қызанақ жапырақтарының ауруларын анықтауда үздік қабілетін көрсетті. Тыңайтқыштарды оңтайландыруда шешім ағаштары, ең жақын көршілер әдісі (K-Nearest Neighbors), CNN, градиенттік күшейту ағаштары (Gradient Boosting Decision Trees) және LogitBoost сияқты машиналық оқыту модельдері негізгі компоненттерді талдау (PCA) арқылы түрлі ерекшеліктермен тексерілді. Алты PCA ерекшелігі бар CNN моделі 97,58% дәлдікке қол жеткізіп, болжамдық модельдеу үшін ерекшеліктерді оңтайландырудың тиімділігін көрсетті. Бұл нәтижелер жасанды интеллект технологияларын ауыл шаруашылығына интеграциялау Қазақстанда өнімділік пен тұрақтылықты айтарлықтай арттыра алатынын, ауруларды дәл анықтауға және ресурстарды оңтайлы пайдалануға мүмкіндік беретінін көрсетеді. Болашақ зерттеулер бұл модельдерді нақты ауыл шаруашылығы жағдайларында енгізуге және оларды басқа дақылдар мен экологиялық жағдайларға бейімдеуге бағытталуы тиіс.

Тірек сөздер: оңтайландыру, компьютерлік көру, машиналық оқыту, терең оқыту, конволюциялық нейрондық желілер, ауыл шаруашылығы, жасанды интеллект, өсімдік ауруларын анықтау, тыңайтқыштарды оңтайландыру, болжамдық модельдеу.

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РЕШЕНИЯ НА ОСНОВЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В СЕЛЬСКОМ ХОЗЯЙСТВЕ: ПРОГНОЗИРОВАНИЕ УДОБРЕНИЙ И ОБНАРУЖЕНИЕ БОЛЕЗНЕЙ ТОМАТОВ С ИСПОЛЬЗОВАНИЕМ МАШИННОГО ОБУЧЕНИЯ И КОМПЬЮТЕРНОГО ЗРЕНИЯ

Аннотация

Это исследование направлено на использование искусственного интеллекта для улучшения сельскохозяйственной практики в Казахстане. Оно сосредоточено на обнаружении болезней листьев томатов и оптимизации удобрений. Модели глубокого обучения, включая GoogleNet (InceptionV3), VGG16, ResNet50, MobileNetV2 и пользовательскую сверточную нейронную сеть (CNN), были оценены для обнаружения болезней. GoogleNet показала самую высокую точность – 99,72%, что показывает ее способность обнаруживать болезни листьев томатов. Для оптимизации удобрения были оценены различные модели на основе машинного обучения, а именно деревья решений, K-ближайшие соседи, CNN, дерево решений Gradient Boosting, LogitBoost с использованием различных функций PCA. Модель CNN, которая использовала шесть функций PCA, достигла наилучшей точности – 97,58%. Это показывает, как хорошие функции могут помочь в прогнозировании. Результаты показывают, что использование технологий ИИ может значительно повысить производительность сельского хозяйства и устойчивость Казахстана за счет точного обнаружения болезней и оптимизированного использования ресурсов. В будущих исследованиях модели следует внедрить в систему сельского хозяйства в режиме реального времени, а также расширить их на большее количество культур и условий.

Ключевые слова: оптимизация, компьютерное зрение, машинное обучение, глубокое обучение, сверточные нейронные сети, сельское хозяйство, искусственный интеллект, обнаружение болезней растений, оптимизация удобрений, предиктивное моделирование.

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