Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549465

AUTOMATED APPROACH TO CLASSIFICATION OF CROPS USING SVM AND NEURAL NETWORK

Rajni Devi, Dr.Harpreet Kaur
Department of Computer Science and Engineering, Punjabi University, Patiala, India

ABSTRACT

Crop fertility detection plays a crucial role in optimizing agricultural practices and maximizing crop yield. In this study, a combination of neural network (NN) and support vector machine (SVM) algorithms is employed to develop an efficient and accurate system for crop fertility detection. The proposed system utilizes input data derived from various sources, such as soil samples, weather conditions, and crop characteristics. These input variables are preprocessed and fed into the NN and SVM models for training. The NN model employs its ability to learn complex patterns and relationships within the data, while the SVM model utilizes its strong classification capabilities. Through a series of experiments and training iterations, the models are trained to classify soil samples into different fertility levels, such as low, medium, and high. The performance of the models is evaluated using evaluation metrics like accuracy, precision, recall, and F1 score. The results demonstrate that the combined NN and SVM approach achieves high accuracy in crop fertility detection. The neural network captures intricate relationships between the input variables, while the support vector machine effectively separates the data into distinct fertility classes. This combination leverages the strengths of both algorithms and enhances the overall detection accuracy. The developed system holds significant potential for real-world applications in agriculture, enabling farmers to make informed decisions regarding fertilizer application, irrigation, and other farming practices. By accurately identifying crop fertility levels, farmers can optimize resource allocation, minimize environmental impact, and maximize crop yield, ultimately contributing to sustainable and efficient agricultural practices.

Keywords: Crop classification, classification accuracy, specificity, SVM, NN

1. INTRODUCTION

Agriculture plays an essential role to any country's economic success. It is a field that has a significant impact on a country's GDP. Agriculture accounts for around 16% of India's GDP[1]. According to the United Nations, the global population in 2030 and 2050 is predicted to be 8.6 billion and 9.8 billion, respectively. In other words, each year, approximately 83 million individuals are included to the world's entire population. The ever-increasing human population and the ever-increasing worldwide demand for food will create huge challenges to humanity, influencing future activities towards food security and preservation of the environment[2]. Crop classification using technology refers to the use of various technological tools and methods to identify and categorize different types of crops[3]. This process is essential for monitoring and managing agricultural fields, optimizing resource allocation, and making informed decisions related to crop management.

One of the commonly employed technologies for crop classification is remote sensing. For the categorization of crops, evaluation of crop health, and estimation of yield, remote sensing is crucial[4]. The use of satellite or aerial photography to obtain knowledge of the Earth's surface is known as remote sensing. With the help of remote sensing, crops can be classified based on their spectral signatures, which are unique reflectance patterns of different crops in various wavelengths of light[5]. By analyzing these spectral signatures using techniques like multispectral or hyperspectral analysis, crops can be identified and classified.

Another technology used for crop classification is machine learning and computer vision. To categorize features, machine learning algorithms such as SVM, and CNN are employed[6] .By training machine learning algorithms on large datasets of crop images, these algorithms can learn to recognize specific crop types based on visual features[7]. Convolutional neural networks (CNNs) are commonly used for this purpose, as they excel in image recognition tasks. These models can classify crops by analyzing visual patterns and textures in images, distinguishing different crop types based on their unique characteristics.

Additionally, sensor technologies such as near-infrared (NIR) sensors and Light Detection and Ranging (LiDAR) can provide valuable data for crop classification. NIR sensors measure the reflectance of crops in the NIR spectrum, which can indicate crop health and moisture levels. LiDAR sensors, on the other hand, can provide detailed 3D information about crops, including their height and structure[8]. These sensor-based technologies can complement remote sensing and visual-based approaches, providing more comprehensive data for accurate crop classification.

Overall, crop classification using technology enables farmers, agronomists, and agricultural researchers to monitor and analyze crops efficiently. It assists in identifying crop types, monitoring their health and growth, and implementing targeted management practices. By leveraging technology for crop classification, farmers can optimize their farming practices, make informed decisions, and improve overall productivity and sustainability in agriculture.

These studies highlight the effectiveness of machine learning techniques, including decision trees, deep learning, ensemble learning, and random forests, in crop fertility detection. By utilizing various data sources, such as soil properties, sensor measurements, and remote sensing imagery, machine learning models can provide valuable insights for optimizing fertilizer application and improving crop yield. These research studies highlight the diverse approaches and techniques used for crop fertility detection, including hyperspectral imaging, remote sensing, machine learning, fuzzy logic, and sensor technologies. The findings emphasize the importance of accurate fertility assessment for optimizing agricultural practices and enhancing crop productivity.

2. LITERATURE SURVEY

Crop fertility detection is an important aspect of precision agriculture that enables farmers to optimize fertilizer application and maximize crop yield. Here is a literature survey highlighting some key research studies on crop fertility detection:

In [9] W.S. Lee et al. proposed this study focuses on using hyperspectral imaging combined with machine learning algorithms to detect crop fertility. Hyperspectral images were acquired from different crop fields, and machine learning models, such as support vector machines

(SVM) and random forests, were trained to classify crops based on their fertility levels. The results showed promising accuracy in fertility detection.

In [10] Suraksha, I.S. et al. proposed this research employs remote sensing data and spatial modeling techniques to map crop fertility. Satellite imagery and soil sampling data were integrated to create fertility maps using geostatistical analysis and regression models. The study demonstrates the potential of remote sensing in providing valuable information for precision agriculture and fertility management.

In [11] A Chunyu et al. proposed this review paper examines various spectral indices used for crop fertility monitoring. It explores the effectiveness of indices such as normalized difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI), and leaf chlorophyll content index (CCI) in assessing crop fertility. The review provides insights into the strengths and limitations of different indices for fertility detection.

In [12] Mrs. N. Saranya et al. describe this study presents a fuzzy logic-based system for evaluating crop fertility. The system incorporates inputs such as soil parameters, climate data, and crop characteristics to generate fertility scores. Fuzzy logic rules were developed based on expert knowledge, and the system demonstrated accurate fertility evaluation for different crop types.

In [13] P.R. Harshani et al. describe this research explores the integration of multiple sensor technologies for crop fertility detection and management. It discusses the combined use of remote sensing, sensor-based measurements (e.g., NIR sensors), and soil sampling techniques to assess and manage crop fertility. The study highlights the potential of sensor integration for precise and real-time fertility monitoring.

In [14] Sai Kirthi Pilli et al. proposed this study applies machine learning algorithms, including decision trees, random forests, and support vector machines, for crop fertility assessment. The research utilizes data such as soil properties, climate variables, and historical crop yields to develop predictive models. The results demonstrate the effectiveness of machine learning in identifying crop fertility.

In [15] Muhammad Attique Khan et al. proposed this study, deep learning techniques, specifically convolutional neural networks (CNN), are employed to classify crops based on fertility using satellite imagery. The CNN model is trained on annotated satellite images and achieves high accuracy in fertility classification. The research highlights the potential of deep learning and remote sensing data for crop fertility detection.

In [16] Clifton Makate et al. proposed this research combines ensemble learning techniques, such as AdaBoost and gradient boosting, with sensor data for crop fertility prediction. Sensor measurements, including soil moisture, temperature, and nutrient levels, are integrated with ensemble learning models to estimate fertility levels. The study demonstrates the effectiveness of ensemble learning in crop fertility detection.

This study utilizes unmanned aerial vehicles (UAVs) and machine learning algorithms for real-time crop fertility monitoring. UAVs capture high-resolution images, and machine learning models, such as k-nearest neighbors and support vector machines, analyze the images to determine crop fertility. The research shows the potential of UAV-based remote sensing and machine learning for on-demand fertility assessment.

In [17] Dai kyung hyung et al. proposed this research focuses on using multispectral remote sensing data and random forest algorithms to assess crop fertility. Spectral information from satellite or UAV imagery is processed, and random forest models are trained to classify crops into fertility categories. The study demonstrates the capability of remote sensing and random forests for accurate fertility detection.

In[18] Gagandeep Kaur et al. describe this research focuses on heatmap to show the relationship between different parameter to predict cement logistics. The technique of heatmap is very practical to our work also and we have also implemented heatmap to show the correlation between different parameter related to classification of crops. It has also been shown in the paper that how different parameters are positively and negatively related to one another.

3. Research Methodology

The research technique defines the whole process used to get the intended results.

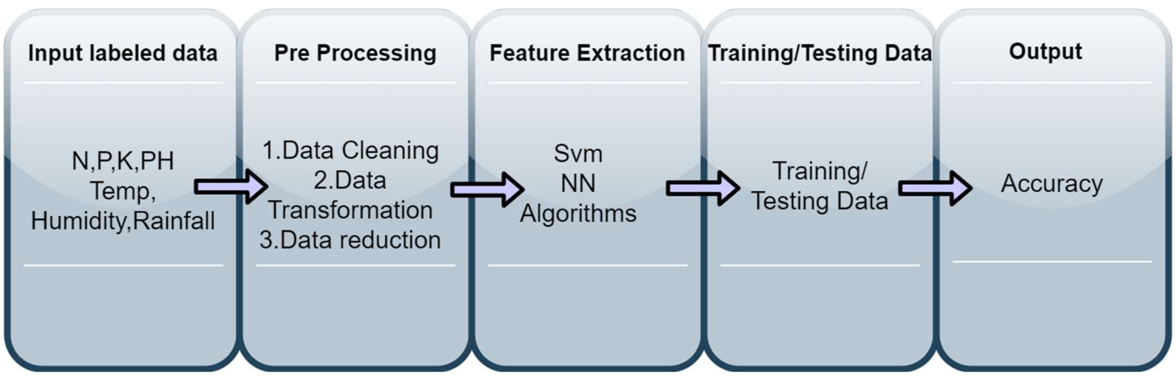

Figure 1: Block diagram of proposed method

(N, P, K, PH), Temperature, Humidity and Rainfall as input to train model.

Data Pre-processing

Data preparation is the process of transforming raw data into an understandable format. The information gathered from various places is frequently incomplete or inconsistent. Therefore, the data must be filtered and normalized before being used for further research. Data pre-processing typically consists of three steps: data cleansing, data transformation, and data reduction. The incomplete data is cleaned during data cleaning in order to normalize the data-set. The term "transformation" refers to the mapping of data homogeneity. Data reduction is the process of taking data and turning it into a more efficient form. Additionally, we separate the data into train and test using the train test split command in accordance with the weight specified in the code. Typically, 80 and 20 percent of the total data are picked for the train and test sets, respectively.

Feature Extraction

The two parameters with the greatest influence on crop classification are temperature and rainfall. In machine learning, there are many different feature extraction algorithms including NN, SVM.

Support Vector Machine

SVM is a supervised machine learning technique that is used for classification and regression applications.

Support Vector Machine (SVM) is a kind of classifier that is a collection of related supervised learning techniques used specifically for classification. SVM will create a dividing hyperplane in space, increasing the boundary between the two data sets. To define the boundary, two parallel hyperplanes are generated, one on either side of the dividing hyperplane across the two data sets[19].

Neural Network

A neural network is a model for computation that is based on the structure and operation of the human brain. It is a strong machine learning algorithm that can perform a variety of tasks such as classification, regression, pattern recognition, and more. This is the most advanced deep learning model we've used to classify diseases. Because it is highly complicated, good computational power is also required. It is the most commonly used neural network for image classification[1] [20]A neural network is made up of layers of linked artificial neurons known as nodes or units. A layer of input, one or more hidden layers, and an output layer are the most common layer configurations. Weighted connectors link each node in a layer to nodes in the next layers.

3.1 Dataset Used

The structure of the dataset that is derived from Kaggle is given in table 1. There are total of 864 records and 8 attributes or columns within the dataset. There are total of 8 attributes. 7 attributes act as predictor and last attribute act as outcome variable.

Table 1: Soil additional attributes

N	**P**	**K**	**temperature**	**humidity**	**ph**	**rainfall**	**Label**
90	42	43	20.87974	82.00274	6.502985	202.9355	Rice
85	58	41	21.77046	80.31964	7.038096	226.6555	Rice
60	55	44	23.00446	82.32076	7.840207	263.9642	Rice
74	35	40	26.4911	80.15836	6.980401	242.864	Rice
78	42	42	20.13017	81.60487	7.628473	262.7173	Rice
69	37	42	23.05805	83.37012	7.073454	251.055	Rice
69	55	38	22.70884	82.63941	5.700806	271.3249	Rice
94	53	40	20.27774	82.89409	5.718627	241.9742	Rice
89	54	38	24.51588	83.53522	6.685346	230.4462	Rice
68	58	38	23.22397	83.03323	6.336254	221.2092	Rice
91	53	40	26.52724	81.41754	5.386168	264.6149	Rice
90	46	42	23.97898	81.45062	7.502834	250.0832	Rice
78	58	44	26.8008	80.88685	5.108682	284.4365	Rice

93	56	36	24.01498	82.05687	6.984354	185.2773	Rice
94	50	37	25.66585	80.66385	6.94802	209.587	Rice
60	48	39	24.28209	80.30026	7.042299	231.0863	Rice
85	38	41	21.58712	82.78837	6.249051	276.6552	Rice
91	35	39	23.79392	80.41818	6.97086	206.2612	Rice
77	38	36	21.86525	80.1923	5.953933	224.555	Rice
88	35	40	23.57944	83.5876	5.853932	291.2987	rice
89	45	36	21.32504	80.47476	6.442475	185.4975	rice
76	40	43	25.15746	83.11713	5.070176	231.3843	rice
67	59	41	21.94767	80.97384	6.012633	213.3561	rice
83	41	43	21.05254	82.6784	6.254028	233.1076	rice
98	47	37	23.48381	81.33265	7.375483	224.0581	rice
66	53	41	25.07564	80.52389	7.778915	257.0039	rice
97	59	43	26.35927	84.04404	6.2865	271.3586	rice
97	50	41	24.52923	80.54499	7.07096	260.2634	rice
60	49	44	20.77576	84.49774	6.244841	240.0811	rice
84	51	35	22.30157	80.64416	6.043305	197.9791	rice

The values of this dataset were in numeric format as the convergence and prediction through SVM model requires numeric fields.

3.2 Flow of proposed work and description

The flow of the proposed work is in terms of neural network that is implemented for the detection of crop fertility. The flow of the proposed work is represented within figure 2

Figure 2: Flow of proposed work

Input Layer: The input layer consists of nodes representing the features or attributes used for crop classification. Each node represents a specific feature such as soil properties, weather conditions, or other relevant factors.
Hidden Layer(s): The hidden layer(s) are intermediary layers between the input and output layers. They consist of multiple neurons or units that perform computations and learn complex patterns and relationships within the data. Depending on the difficulty of the classification problem, the number of hidden layers and neurons per layer may vary.
Output Layer: The output layer represents the different crop classes to be classified. Each node in the output layer corresponds to a specific crop class. The number of nodes in the output layer is determined by the number of distinct crop classes.
Weights: Each connection between nodes in different layers is associated with a weight. These weights determine the strength of the connection and are adjusted during the training process to minimize the error in classification.
Bias Neurons: Bias neurons are additional nodes introduced in each layer (except the input layer) to help the neural network learn and make accurate predictions. Bias neurons contribute a constant value to the activation of the next layer, allowing for more flexibility in modeling complex relationships.
Activation Function: The activation function introduces non-linearity to the neural network, enabling it to learn and approximate non-linear relationships between input features and crop classes. Common activation functions include sigmoid, ReLU (Rectified Linear Unit), and softmax functions.
The diagram represents a basic feed-forward neural network architecture commonly used for crop classification tasks. The specific configuration and architecture of the neural network may vary depending on the specific requirements of the crop classification problem and the chosen implementation framework or library.

4. Mathematical formulation

Neural Network Formulation:
The neural network with a single hidden layer is presented in this section. The inputs to the neural
network are the features of the crop, and the output is the predicted fertility of the crop.
a) Forward Propagation:
The inputs to the neural network are denoted as X, which is an n-dimensional feature vector representing the crop characteristics. Weights and biases of the neural network are represented as W
and b, respectively.
The hidden layer's output is computed as follows:
Z = $\boldsymbol{XW_1 + b_1}$
A = activation function(Z)
The output layer is calculated as:

Y = $AW_2 + b_1$
b) Activation Function:
The activation function is a non-linear function that introduces non-linearity into the neural network.
Sigmoid, tanh, and ReLU (Rectified Linear Unit) are examples of popular activation functions.
c) Loss Function:
The loss function measures the difference between the predicted fertility (Y) and the actual fertility
values (Y_actual). The loss function selected depends on the particular situation and can include mean
squared error (MSE), binary cross-entropy, or categorical cross-entropy.
d) Backpropagation and Gradient Descent:
The backpropagation algorithm is used to calculate the gradients of the weights and biases with respect
to the loss function. Gradient descent is then used to update the weights and biases in the opposite
direction of the gradients, minimizing the loss function.

Support Vector Machine (SVM) Formulation:
SVM is a supervised machine learning algorithm that aims to find an optimal hyperplane that separates
the data into different classes. In the case of crop fertility detection, we can use SVM to classify crops
into fertile or infertile categories.
a) Data Representation:
Let's assume that we have a training dataset with m samples and n features. Each training sample is denoted
as (x_i, y_i), where x_i represents the feature vector, and y_i is the corresponding fertility label (-1 for infertile,
+1 for fertile).
b) Optimization Problem:
SVM aims to find the hyperplane that maximally separates the two classes while minimizing the
misclassification error. It can be expressed as the optimization issue shown below.

minimize: 0.5 * $||w||$^2 + C *$\sum\left(max\left(0, 1 - y\_i\ *\ (w\text{^}T *\ \ x\_i\ +\ \ b)\right)\right)$
subject to: y_i * $(x\text{^}T\ * x\_i + b)$ ≥1, for all i

where w represents the weights, b is the bias term, C is the regularization parameter that balances the
trade-off between maximizing the margin and minimizing the classification error, and ||w||^2 is the
regularization term.

c) Kernel Trick:
In many cases, the data may not be linearly separable in the original feature space. SVM uses the kernel
trick to map the data into a higher-dimensional space where it may become linearly separable. Kernels that are frequently used are linear, polynomial, and radial basis function (RBF) kernels.
d) Prediction:
To make predictions on new, unseen data, the sign of the decision function f(x) = w^T * x + b is used. If
f(x) is positive, the sample is classified as fertile; otherwise, it is classified as infertile.
Next section gives the performance analysis and results corresponding to the neural network and
support vector machine.

5. PERFORMANCE ANALYSIS AND RESULTS

Performance analysis of neural networks and support vector machines (SVM) for crop fertility detection involves evaluating several metrics to compare the effectiveness of the two algorithms. Here are some key performance metrics commonly used for such analysis:
5.1 Result from simulation

Correlation analysis is a statistical method for determining the degree and direction of a relationship among two variables. In the context of crop fertility detection, correlation analysis can provide insights into the relationships between different factors and crop fertility levels.
The simulative result indicates correlation analysis at first place in terms of heatmap as shown in Figure 3. The high correlation values both positive or negative indicates that crops are significantly affected with that parameter. The value of -0.23 in level “N” is indicating that low correlation negative value which means if these metric increases, crop fertility decreases. Positive correlation between rainfall and “N” indicating that both factor increases the crop fertility.

Figure 3: Correlation analysis

After the correlation analysis, accuracy levels and loss levels are examined with each iteration. The accuracy levels increase with each iteration and loss levels decreases. This means overall detection process shows significant improvement with the detection process.

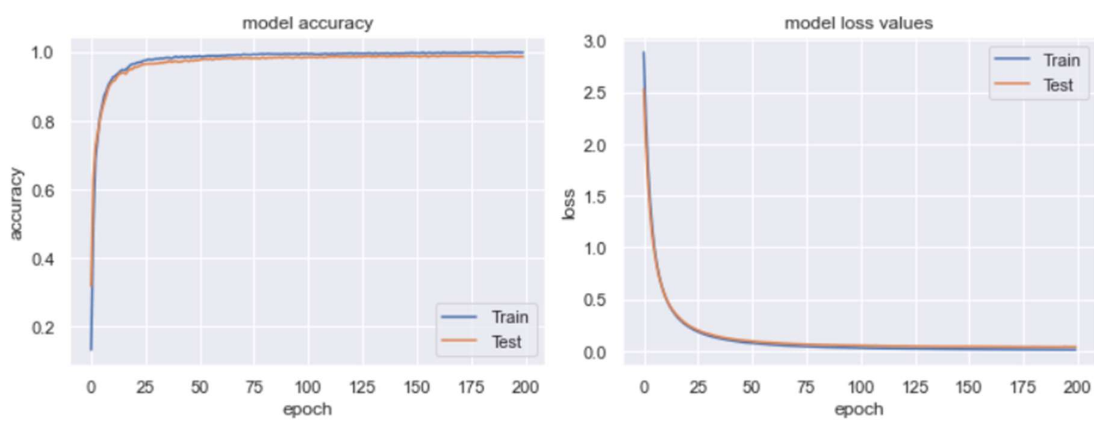

Figure 4: Representation of model accuracy and loss function

Figure 4 elaborates that 99% accuracy in terms of prediction and only 1% loss occurs with the model in terms of predictions.

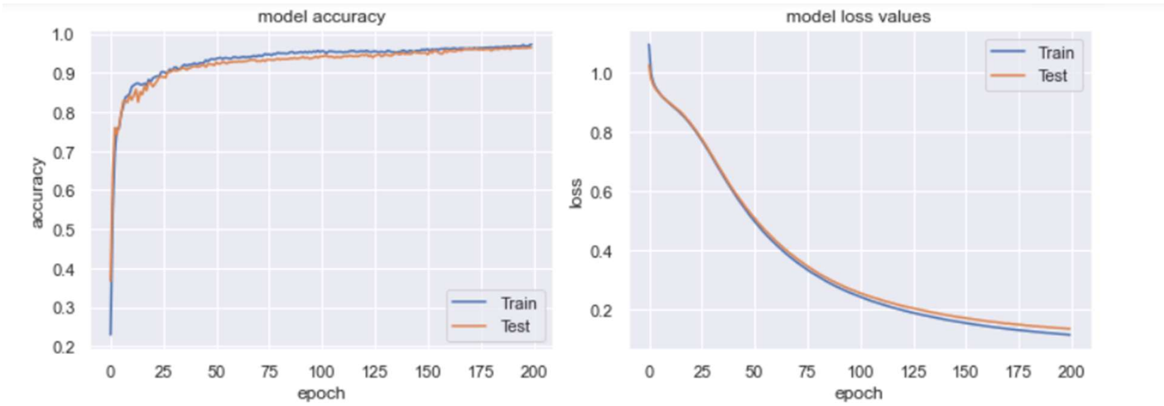

Figure 5: Representation of Flow

The above figure 5 indicates the flow in terms of model accuracy and loss after 50 iterations of the model. This accuracy remains consistent after 50 iterations as indicated both in figure 5 and figure 6.

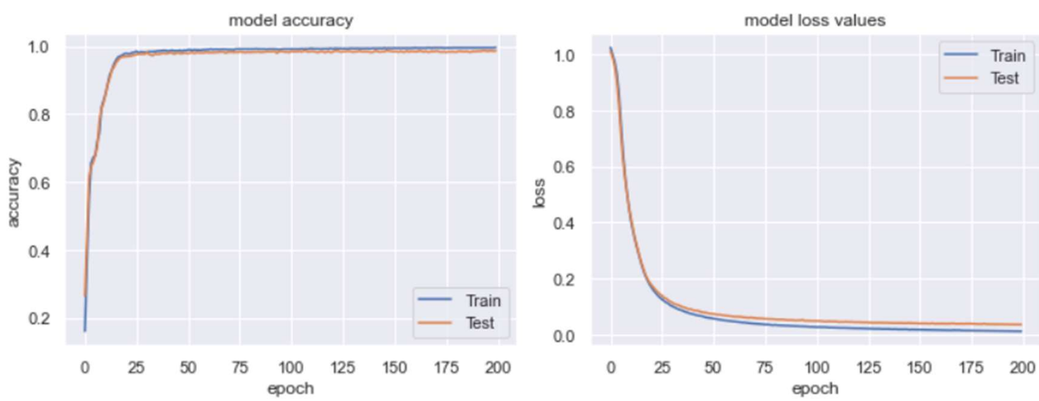

Figure 6: Model representation after 100 iterations

The model accuracy improves after 100 iterations by the margin of 10%. The model loss is also reduced by the application of the proposed model.

5.2 Results and Discussion

This section describes the classification accuracy comparison for SVM and neural network (NN) models for crop fertility detection as represented in Table 2. The table presents the classification accuracy results for SVM and neural network models in crop fertility detection. Accuracy represents the proportion of correctly classified instances out of the total number of instances.

Table 2: Result in terms of classification accuracy

Algorithm	**Accuracy**
SVM	0.85
NN	0.92

The plot corresponding to the classification accuracy for neural network and support vector machine is given in figure 7.

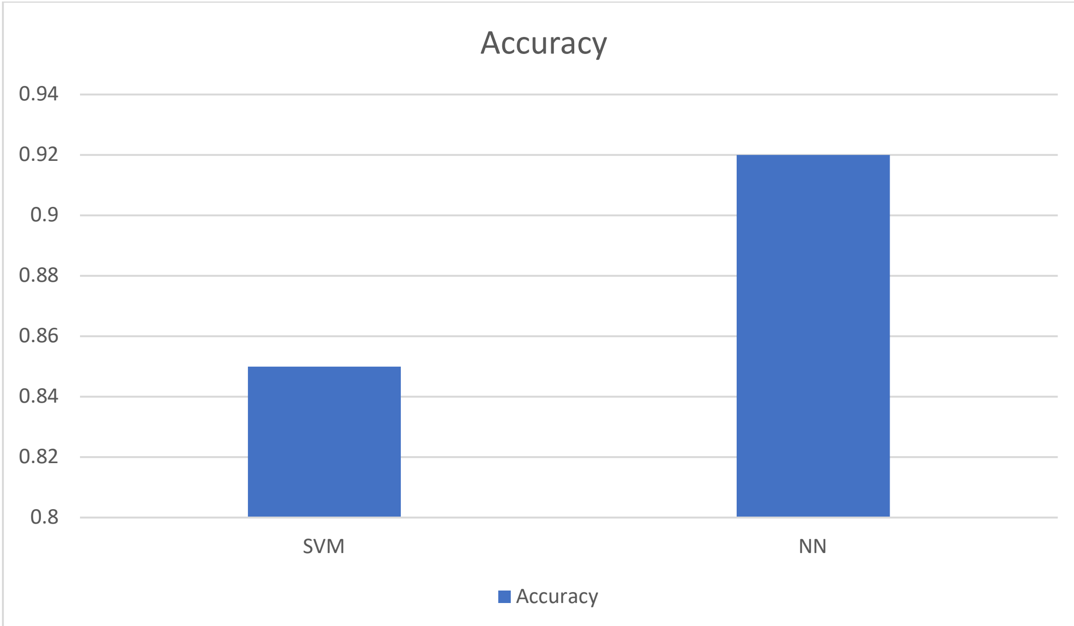

Figure 7: Classification accuracy results

SVM Accuracy: The SVM model achieved an accuracy of 0.85, indicating that it correctly classified 85% of the crop fertility instances in the evaluation dataset. This suggests that the SVM model performs reasonably well in predicting crop fertility levels.
NN Accuracy: The neural network model achieved a higher accuracy of 0.92, indicating that it correctly classified 92% of the crop fertility instances in the evaluation dataset. This suggests that the neural network model outperforms the SVM model in terms of accuracy for crop fertility detection.
Specificity and sensitivity comparison of SVM and neural network (NN) models for crop fertility detection is shown in Table 3. It shows that Specificity measures the proportion of correctly classified negative instances (infertile crops) out of all actual negative instances. Sensitivity, also known as recall or true positive rate, measures the proportion of correctly classified positive instances (fertile crops) out of all actual positive instances.

Table 3: Specificity and sensitivity comparison

Algorithm	Specificity	Sensitivity
SVM	0.88	0.82
NN	0.92	0.88

The plot corresponding to the specificity and sensitivity is given in figure 8

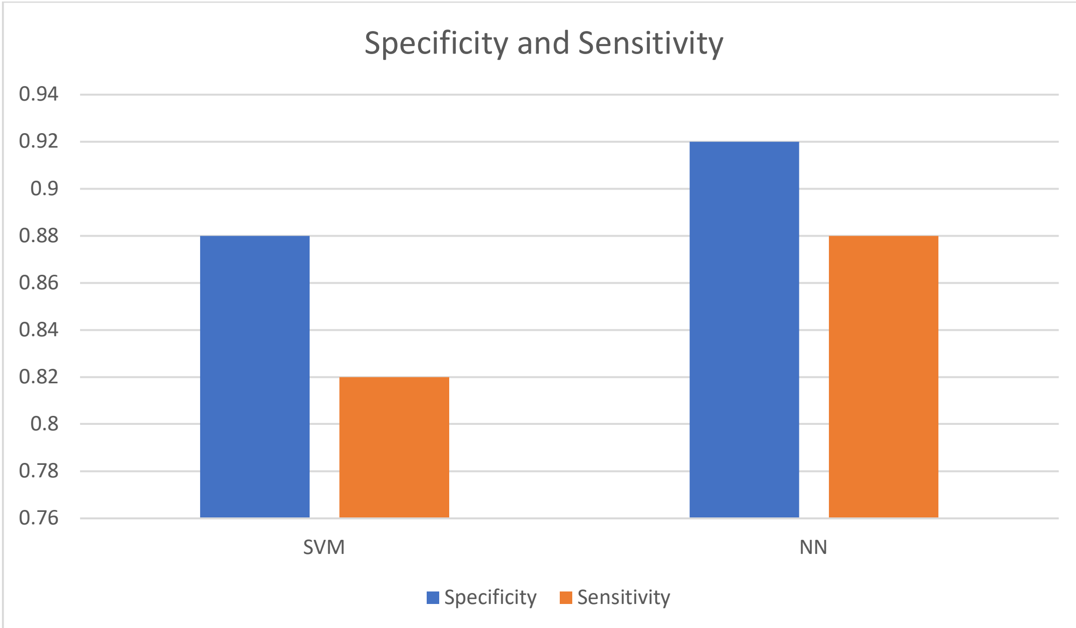

Figure 8: Sensitivity and specificity comparison

SVM Specificity and Sensitivity: The SVM model achieved a specificity of 0.88, indicating that it correctly classified 88% of the infertile crop instances. It also achieved a sensitivity of 0.82, indicating that it correctly classified 82% of the fertile crop instances.

NN Specificity and Sensitivity: The neural network model achieved a higher specificity of 0.92, indicating that it correctly classified 92% of the infertile crop instances. It also achieved a higher sensitivity of 0.88, indicating that it correctly classified 88% of the fertile crop instances.

The comparison table provides insights into the performance of SVM and neural network models in terms of specificity and sensitivity. It shows that the neural network model outperforms the SVM model in both specificity and sensitivity, suggesting better performance in correctly classifying both fertile and infertile crops.

6. CONCLUSION

In conclusion, the comparison between SVM and neural network models for crop fertility detection reveals the following insights:

Accuracy: The neural network model achieved a higher accuracy (92%) compared to the SVM model (85%). This indicates that the neural network model is more effective in classifying crop fertility levels accurately. Specificity and Sensitivity: The neural network model demonstrated higher specificity (92%) and sensitivity (88%) compared to the SVM model (specificity: 88%, sensitivity: 82%). This suggests that the neural network model performs better in correctly classifying both infertile and fertile crops.

Based on these findings, the neural network model outperforms the SVM model in terms of accuracy, specificity, and sensitivity for crop fertility detection. However, it's important to consider other factors such as computational requirements, interpretability, and dataset characteristics when choosing between the two algorithms.

It is worth noting that these conclusions are based on the specific dataset and experimental setup used for evaluation. The performance comparison may vary with different datasets, feature selections, hyperparameter tuning, and implementation details. Therefore, further research and experiments are recommended to validate the performance of the models on different datasets and assess their suitability for specific crop fertility detection applications.

REFERENCES

[1] Amity University and Institute of Electrical and Electronics Engineers, *10th International Conference on Cloud Computing, Data Science & Engineering : proceedings of the Confluence 2020 : 29-31 January 2020, Amity University, Uttar Pradesh, India.*

[2] A. Orynbaikyzy, U. Gessner, and C. Conrad, "Crop type classification using a combination of optical and radar remote sensing data: a review," *International Journal of Remote Sensing*, vol. 40, no. 17. Taylor and Francis Ltd., pp. 6553–6595, Sep. 02, 2019. doi: 10.1080/01431161.2019.1569791.

[3] V. Sellam and E. Poovammal, "Prediction of crop yield using regression analysis," *Indian J Sci Technol*, vol. 9, no. 38, 2016, doi: 10.17485/IJST/2016/V9I38/91714.

[4] S. Murmu and S. Biswas, "Application of Fuzzy Logic and Neural Network in Crop Classification: A Review," *Aquat Procedia*, vol. 4, pp. 1203–1210, 2015, doi: 10.1016/j.aqpro.2015.02.153.

[5] M. Kaur, H. Gulati, and H. Kundra, "Data Mining in Agriculture on Crop Price Prediction: Techniques and Applications," *Int J Comput Appl*, vol. 99, no. 12, pp. 1–3, Aug. 2014, doi: 10.5120/17422-8273.

[6] S. S. Harakannanavar, J. M. Rudagi, V. I. Puranikmath, A. Siddiqua, and R. Pramodhini, "Plant leaf disease detection using computer vision and machine learning algorithms," *Global Transitions Proceedings*, vol. 3, no. 1, pp. 305–310, Jun. 2022, doi: 10.1016/j.gltp.2022.03.016.

[7] N. Sharma, A. Chakrabarti, and V. E. Balas, Eds., "Data Management, Analytics and Innovation," vol. 1016, 2020, doi: 10.1007/978-981-13-9364-8.

[8] T. K. Fegade and B. V. Pawar, "Crop Prediction Using Artificial Neural Network and Support Vector Machine," *Advances in Intelligent Systems and Computing*, vol. 1016, pp. 311–324, 2020, doi: 10.1007/978-981-13-9364-8_23/COVER.

[9] W. S. Lee, V. Alchanatis, C. Yang, M. Hirafuji, D. Moshou, and C. Li, "Sensing technologies for precision specialty crop production," *Computers and Electronics in Agriculture*, vol. 74, no. 1. pp. 2–33, Oct. 2010. doi: 10.1016/j.compag.2010.08.005.

[10] S. I. S. Sushma B, "Disease Prediction of Paddy Crops Using Data Mining and Image Processing Techniques," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 5, no. 5, pp. 3494–3502, 2016, doi: 10.15662/IJAREEIE.2016.0505006.

[11] H. Chunyu, F. Jiandong, L. Bajin, and Z. Yudong, "Network data acquisition method based on crop pest control knowledge," *ACM International Conference Proceeding Series*, May 2021, doi: 10.1145/3469213.3470368.

[12] N. Saranya and A. Mythili, "Classification of Soil and Crop Suggestion using Machine Learning Techniques," *International Journal of Engineering Research and*, vol. V9, no. 02, pp. 671–673, 2020, doi: 10.17577/ijertv9is020315.

[13] P. R. Harshani, T. Umamaheswari, R. Tharani, S. Rajalakshmi, and J. Dharani, "Effective Crop Productivity and Nutrient Level Monitoring in Agriculture Soil Using IOT," in *ICSNS 2018 - Proceedings of IEEE International Conference on Soft-Computing and Network Security*, Institute of Electrical and Electronics Engineers Inc., Dec. 2018. doi: 10.1109/ICSNS.2018.8573674.

[14] S. K. Pilli, B. Nallathambi, S. J. George, and V. Diwanji, "eAGROBOT- A Robot for Early Crop Disease Detection using Image Processing," *IEEE Access*, no. Icecs, pp. 1684–1689, 2015.

[15] M. A. Khan *et al.*, "CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features," *Comput Electron Agric*, vol. 155, pp. 220–236, Dec. 2018, doi: 10.1016/j.compag.2018.10.013.

[16] C. Makate, R. Wang, M. Makate, and N. Mango, "Crop diversification and livelihoods of smallholder farmers in Zimbabwe: Adaptive management for environmental change," *Springerplus*, vol. 5, no. 1, pp. 1–18, Jul. 2016, doi: 10.1186/S40064-016-2802-4/TABLES/4.

[17] D. K. Hyun, S. J. Ryu, H. Y. Lee, and H. K. Lee, "Detection of upscale-crop and partial manipulation in surveillance video based on sensor pattern noise," *Sensors (Switzerland)*, vol. 13, no. 9, pp. 12605–12631, 2013, doi: 10.3390/s130912605.

[18] G. Kaur, H. Kaur, and S. Goyal, "Correlation analysis between different parameters to predict cement logistics," *Innov Syst Softw Eng*, Mar. 2022, doi: 10.1007/s11334-022-00505-y.

[19] IEEE Staff and IEEE Staff, *2012 International Conference on Pattern Recognition, Informatics and Medical Engineering.*

[20] V. Mazzia, A. Khaliq, and M. Chiaberge, "Improvement in land cover and crop classification based on temporal features learning from Sentinel-2 data using recurrent-Convolutional Neural Network (R-CNN)," *Applied Sciences (Switzerland)*, vol. 10, no. 1, Jan. 2020, doi: 10.3390/app10010238.