https://doi.org/10.31449/inf.v48i4.5132 Informatica **48** (2024) 653–662 **653**

Classification and Identification of Weeds Using Machine Learning Classifiers

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Keywords: cnn, uav, machine learning algorithms

Received: September 2, 2023

Weeds pose significant challenges in agriculture, impacting crop yields and increasing the reliance on herbicides. Accurate and timely identification of weeds is crucial for effective weed management strategies. This study proposed a novel approach for automated identification of weeds using various machine learning classifiers. Our study explores the effectiveness of diverse algorithms, including Support Vector Machine (SVM), Random Forest, Decision Tree, k-Nearest Neighbors (KNN), Extra Tree, and Gaussian Naive Bayes (NB). By pre-processing and engineering features from a diverse dataset of weed images, we ensure optimal model performance. Through rigorous experimentation and evaluation, we assess the performance of each classifier in weed identification. Notably, the Extra Tree classifier achieves an impressive accuracy of 96.35% and an outstanding kappa coefficient of 96.21%. These findings offer valuable insights into the effectiveness of different classifiers and their potential applications in precision agriculture for targeted weed management and crop optimization

Povzetek: Analizirana je uporaba strojnega učenja za avtomatizirano prepoznavanje plevela v kmetijstvu, vključno s SVM, naključnimi gozdovi in CNN, ter uporaba UAV slik.

1 Introduction

Weed identification plays a pivotal role in agriculture and environmental management, involving the distinction of unwanted plant species from desired vegetation. The conventional manual process is laborious and time-intensive, prompting the integration of machine learning and computer vision techniques for automated identification. Utilizing tools like Convolution Neural Networks (CNNs) and ensemble classifiers, modern approaches analyze visual features, leaf shapes, and textures in captured images to efficiently detect and classify weeds. This technological advancement enhances accuracy and expedites the identification process, with applications extending to agriculture, ecological conservation, and land management for optimized resource utilization and sustainable practices [1]. In a study by [2], the utilization of a Random Forest Classifier for weed identification yielded an initial accuracy of 82% and a kappa coefficient of 0.73 in preliminary assessments. A study [3] used tiny YOLOv3 for Convolvulus sepium detection in sugar beet fields. They combined 2271 synthetic images with 452 field images for model training. YOLO anchor box sizes were determined via k-means clustering on the training dataset. Testing on 100 field images showed that using the combination of synthetic and original images provided improved mAP from 0.751 to 0.829 compared to using field images alone. In a study detailed in [4], the differentiation of crops and weeds based on visible and near-infrared spectrums is achieved through the application of Support Vector Machine, Artificial Neural Network, and Decision Tree techniques. The research attains a notable accuracy of 68.40%. The investigation outlined in [5] delves into an automated weed detection system that employs Convolutional Neural Networks (CNN) with Unmanned Aerial Vehicle (UAV) imagery. The proposed CNN LVQ (Learning Vector Quantization) model emerges as a remarkable contender for effectively classifying various categories. Notably, the soil class achieves an impeccable 100% user accuracy, closely trailed by soybean (99.79%), grass (98.58%), and broadleaf (98.32%). After meticulous hyper parameter refinement, the developed CNN LVQ model achieves an exceptional overall accuracy of 99.44% for weed detection, decisively surpassing the performance of previously documented studies. Within the domain of machine learning, a multitude of techniques are harnessed for weed identification. An illustrative instance involves the application of machine learning methodologies for weed detection in an Australian chilli crop field. In this context, diverse algorithms, including random forest (RF), support vector machine (SVM), and k-nearest neighbours (KNN), are systematically explored to ascertain their efficacy in leveraging UAV images for weed detection. The achieved results underscore notable accuracies: 96% for RF, 94% for SVM, and 63% for KNN, as documented in reference [6]. In a recent scholarly investigation [7], the identification of weeds within vegetable plantations was accomplished employing Centre Net, a fusion of deep learning and image proce

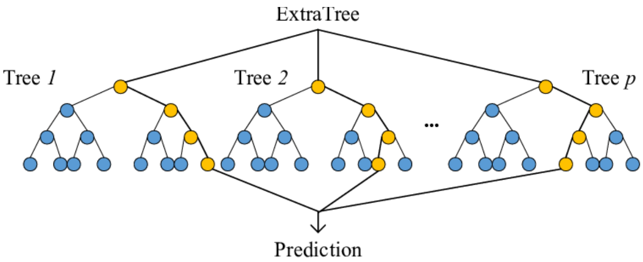

Figure 1: Extra tree classifier

Remarkable outcomes, with a precision of 95.6%, a recall of 95.0%, and an impressive F1 score of 0.953. To further enhance Bayesian classification accuracy, Genetic Algorithms (GAs) were skilfully employed to optimize the colour index. A hybrid CNN-SVM classifier is proposed for weed recognition in winter rape fields, aiming to improve accuracy. Utilizing VGG network model, the approach achieved average accuracies of 99.2% in training and 92.1% in classification [8]. This [9] overview explores RNN- and CNN-based weed detection within crop enhancement, showcasing deep learning's potential for agriculture challenges. The Convolutional Neural Network emerges as the most Efficient technique for weed detection, leading to the development of a smart system for in-place weed identification and spraying. In study [10], the SLIC-RF algorithm is proposed for differentiating crops and weeds in upland rice fields using UAV imagery, achieving accuracies up to 0.915. The approach combines HSV-based SLIC with various features, demonstrating potential for effective site-specific weed management. In their study [11] proposed an automatic weed mapping method using UAV imagery in oat fields. Four classification algorithms were tested, with the automatic object-based approach achieving the highest accuracy of 89.0% and 87.1% for two subsets, enabling potential use in precision weed treatment. In their work [12] developed a vision-based weed detection system for soybean crops using custom lightweight deep learning models. Their proposed 5-layer CNN architecture achieved a high accuracy of 97.7% with minimal latency and memory usage, promising efficiency and productivity enhancements in the soybean industry. In their work [13] introduced a method utilizing deep features and one-class classification on unsupervised data for weed detection in UAV images. The approach achieved up to 90% accuracy on test datasets, comparable to supervised models, by employing one-class classifier trained on crop row-detected unsupervised data. This research [14] assesses the Random Forest (RF) classifier's effectiveness in classifying forest cover from Land sat TM imagery, achieving a 96% accuracy using auxiliary data and systematically collected aerial photography. The study presents an operational and cost-effective approach for generating accurate forest cover maps across diverse sclerophyll forests using open-source software. In [15] The realm of smart agriculture, a revolutionary robotic system diminishes reliance on traditional spraying methods like pesticides and herbicides, aiming to meet global food demands and enhance crop production. To achieve this, a Deep Learning (DL) approach utilizing a blend of Convolutional Neural Networks (CNN) and Long-Short-Term Memory (LSTM) is proposed for weed identification and classification. The method achieves an impressive 99.36% average classification accuracy across nine weed categories, surpassing other established techniques. A study [16] employed YOLOv3 deep learning to identify volunteer cotton plants amidst corn fields using UAV-captured RGB images, achieving over 80% detection accuracy and highlighting the potential of DL for real-time pest mitigation via computer vision and UAV technology.

In this context, this study introduces a hybrid methodology that integrates Convolutional Neural Networks (CNN) with the Extra Trees classifier to address the task of identifying weeds within agricultural fields. The CNN part specializes in capturing distinguishing features from input images, and the Extra Trees classifier employs these acquired features to execute the classification process. By merging the advantages of deep learning and the Extra Trees approach, this novel method strives to achieve both accurate and efficient weed identification outcomes.

Leveraging advanced technologies such as Convolutional Neural Networks (CNNs) and the Extra Trees classifier offers a promising avenue for automating weed identification in agriculture. This approach, combining CNNs and Extra Trees, has the potential to enhance accuracy, streamline efficiency, and optimize resource utilization. Consequently, it holds the key to transforming weed management practices and driving improved agricultural productivity.

This study presents an innovative approach that merges Convolutional Neural Networks (CNN) for feature extraction and classification with the Extra Trees classifier to identify weeds in diverse crops, with a specific focus on soybean. Additionally, it differentiates between grass and broadleaf weeds. The dataset encompasses 4400 UAV images, spanning categories like soybean, soil, grass and broadleaf. Notably, the method enhances the performance of the Extra Trees classifier.

This optimized setup improves training effectiveness and maximizes the utility of the extensive UAV weed dataset. The subsequent sections of the paper are structured as follows: Section 2 introduces the CNN model, while Section 3 describes various machine learning algorithms, followed by Section 4 which elaborates the dataset used, and Section 5 presents the methodology employed in this paper. Section 6, presents the experimental results. Subsequently, Section 7 discusses the results and discussion and the conclusion is provided in Section 8.

2 Convolutional neural network

This research leverages the capabilities of Convolutional Neural Networks (CNNs) to serve as a comprehensive framework for both feature extraction and classification. CNNs have garnered substantial recognition for their prowess in processing grid-like data, particularly images, and have exhibited exceptional performance in critical computer vision tasks such as object detection and image classification. In this study, a sophisticated CNN architecture is employed, comprising several pivotal layers, namely convolutional layers, pooling layers, Global Average Pooling (GAP) layers, and fully Connected layers. The architecture begins with the implementation of multiple Convolutional layers, strategically employing learnable filters to extract essential features at distinct spatial resolutions. Three Convolutional layers are thoughtfully configured, with each layer tailored to specific characteristics. Subsequently, pooling layers are introduced to the design, tasked with spatially down-sampling the feature maps while preserving vital information that underpins accurate classification. Of notable importance is the incorporation of the Global Average Pooling (GAP) layer, a fundamental component that furthers feature consolidation. By performing average pooling across the entirety of the feature map, the GAP layer efficiently condenses spatial information while retaining the most critical features. This contributes to the network's resilience against translation variances, thereby enhancing its ability to generalize.

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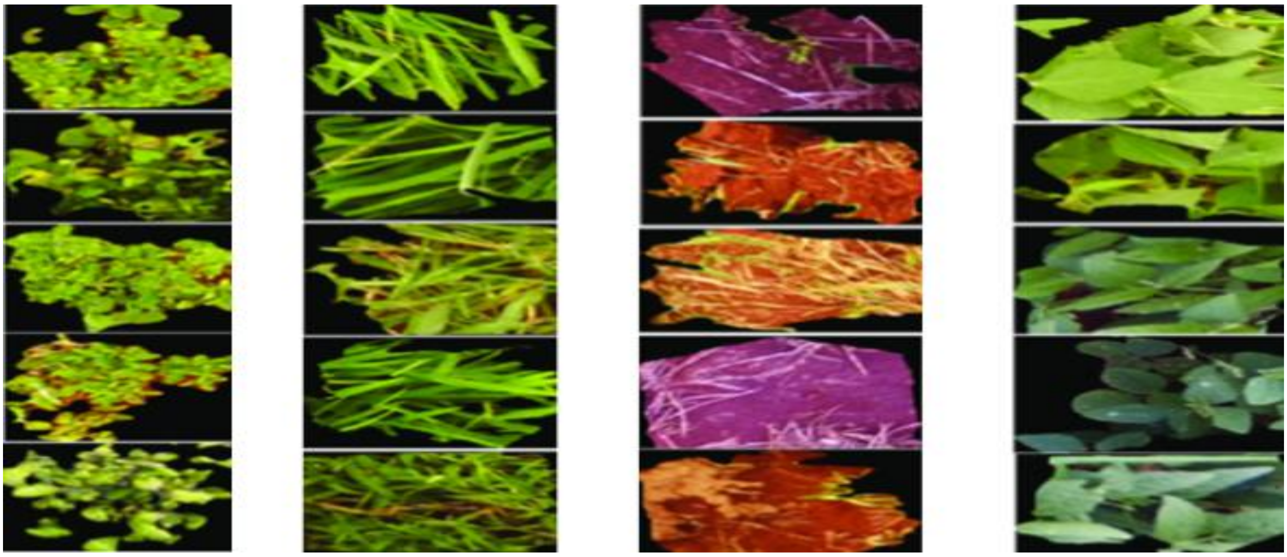

Figure 2: Raw UAV Images of Broadleaf, Grass, Soil, Soya bean

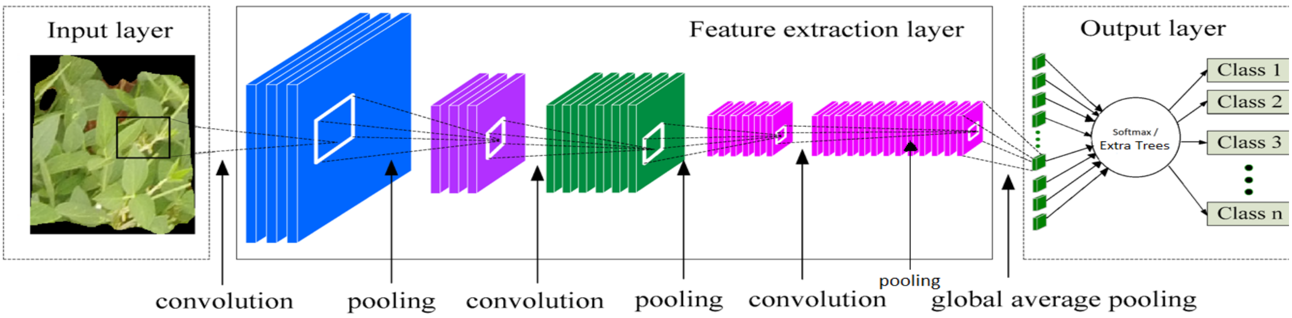

Figure 3: Architecture of proposed model

Building on these foundations, the architecture integrates fully connected layers, which serve to aggregate the extracted features and drive accurate predictions. Through the application of softmax activation, these fully connected layers translate the feature amalgamation into class probabilities, particularly beneficial for multi-class classification tasks.

This unified framework embodies the remarkable Potential of CNNs in deciphering complex features and facilitating precise classification, thereby serving as a cornerstone in advancing state-of-the-art image analysis methodologies.

3 Machine learning algorithms used

Machine learning algorithms are computational models designed to enable computers to learn from data and improve their performance on specific tasks without being explicitly programmed. They fall into categories such as supervised learning, where algorithms are trained on labeled data to make predictions, unsupervised learning, where they find patterns in unlabeled data, semi-supervised learning, combining elements of both supervised and unsupervised learning, reinforcement learning, where agents learn to take actions to maximize rewards, and deep learning, which involves training deep neural networks. The choice of algorithm depends on the problem at hand, available data, and desired outcomes. The successful application of machine learning has transformed various industries, allowing computers to make complex decisions and predictions once exclusive to human intelligence.

3.1 SVM

Support Vector Machines (SVMs) are classification algorithms that seek the best hyper plane to separate different classes by maximizing the margin. They focus on support vectors, near the decision boundary. SVMs handle high dimensions, outliers, and complex data via kernels. While binary by design, they extend to multi-class scenarios using strategies like One-vs-Rest or One-vs-One.

3.2 Random forest

The Random Forest classifier is an ensemble learning algorithm that combines multiple decision trees, each trained on random subsets of data and features. This aggregation of predictions improves accuracy, reduces over fitting, and offers insights into feature importance, making it a robust and popular choice for classification and regression tasks.

3.3 Decision tree

A Decision Tree is a machine learning algorithm that uses a tree-like structure to make decisions based on features. Each internal node represents a decision, branches indicate outcomes, and leaf nodes give predictions. While intuitive and suitable for non-linear data, they can over fit and struggle with generalization.

3.4 Gaussian naive bayes

Gaussian Naive Bayes is a probabilistic classification algorithm based on Bayes' theorem. It assumes that features follow a Gaussian distribution and are conditionally independent given the class label. It's particularly useful for continuous numerical data and works well even with limited training data. Despite its simplicity and the naive assumption, it often performs surprisingly well in real-world scenarios and is a popular choice for text and image classification tasks.

3.5 KNN

K-Nearest Neighbours (KNN) is a supervised algorithm for classification and regression. It identifies the K closest training data points to a query point and predicts Using the majority class or average value of neighbors. KNN assumes similar data points share outcomes, offering simplicity but sensitivity to distance metric and K value.

3.6 Extra tree

The Extra Trees classifier, short for Extremely Randomized Trees classifier, is an ensemble learning algorithm used for classification tasks. It builds multiple decision trees using random subsets of features and data. Unlike Random Forest, Extra Trees selects random splits at each node, reducing variance and enhancing generalization. This randomness also makes it computationally efficient. The algorithm aggregates predictions from all trees to make the final classification decision, resulting in improved accuracy and reduced over fitting. Extra Trees is shown in Figure 1.

4 Dataset

This study employs a dataset sourced from [21], consisting of 400 UAV snapshots of soybean crops captured from a 4 m altitude using the DJI Phantom 3 Professional. The images have a ground sampling distance of 1 cm, as shown in Fig. 2. The images underwent segmentation using the SLIC algorithm, resulting in 15,336 segments in the dataset. Of these segments, 7,376 correspond to soybean, 3,520 to grass, 3,249 to soil, and 1,191 to broadleaf weeds. For more comprehensive dataset information, refer [21]. The dataset is used for weed identification in soybean crops, as well as distinguishing the crops from grass, soil, and broadleaf weed classes. Using classifier ensemble approach rice crop yield is predicted in India [22].

5 Methodology

In this study, 15,334 images were randomly selected from a total collection of 15,336 photographs within the dataset. The dataset encompasses four classes: broadleaf, grass, soil, and soybean. The dataset was divided into a ratio of 80:20 for training and testing. The images were processed, and a CNN with 12 layers was developed for imagery classification (Fig. 3). The model was built using Keras 2.3.0 API with Tensor Flow 2.0 backend and Python 3.8. It consists of three hidden convolution layers, three max-pooling layers, a Global Average Pooling (GAP) layer, and dense layers. The Convolutional layers employ the Rectified Linear Unit (ReLU) activation function to capture complex patterns through non-linearity. Max-pooling layers are used to down-sample feature maps and reduce spatial dimensions. A GAP layer is applied after the final max-pooling layer. This approach allows the model to efficiently learn and retain essential information while reducing dimensions. The ReLU activation function is defined as (F(x) = max (0, x)), which maintains higher values and sets negative ones to zero, enabling complex learning. The code snippet specifies the activation='ReLU' parameter while adding convolutional layers using Tensor Flow’s Keras API. Incorporating max-pooling layers helps down-sample feature maps, reducing spatial dimensions while retaining crucial data. Max pooling selects the most significant value within small regions of the input feature maps, effectively reducing dimensions while preserving relevant information. A GAP layer is introduced to Capture global features after the final max-pooling layer. The Global Average Pooling (GAP) layer serves a fundamental purpose: condensing feature map spatial dimensions while capturing global features. Following the GAP layer, the procedure entails conducting global average pooling across feature maps, yielding a single value for each channel. This operation reduces spatial complexity and encapsulates the overarching presence of acquired features in the input image. Consequently, the GAP layer generates a 1D vector, representing the globally averaged features extracted from feature maps. This vector subsequently serves as input for succeeding fully connected layers, where the extracted features are processed and applied to classification. Thus, the GAP layer's pivotal role lies in bridging convolutional layers and fully connected layers, furnishing a concise and informative depiction of input data.

In the proposed approach, Convolutional Neural Networks (CNN) is employed for feature extraction and classification, while the Extra Trees classifier is adopted as the classification algorithm. The architecture comprises initial and subsequent fully-connected dense layers, followed by the Extra Trees layer, which serves as the output layer for prediction. Additionally, a Competition layer is integrated, featuring four neurons Representing distinct classes. Various epoch counts for the Extra Trees classifier were tested, including 50, 100, and 200. However, after experimentation, it was found that setting the epoch count to 300 yielded higher training and validation accuracy. The learning rate was set at 0.001, and the input vector was initialized using random values. The decision to utilize 300 epochs considerably enhanced the model's accuracy during both training and testing stages.

6 Experimental results

In the experimental results, the proposed approach integrates Convolutional Neural Networks (CNN) for both feature extraction and classification, along with the Extra Trees classifier. The CNN model is initially trained to extract meaningful features from input images through Convolutional and pooling layers. However, it's important to note that the Extra Trees involve training by assigning epochs as the CNN model does. To address this, CNN is employed not only for feature extraction but also for classification, while the Extra Trees classifier is harnessed as the predictive model. This configuration allows for the generation of training and validation graphs, which are crucial for visualizing the learning process.

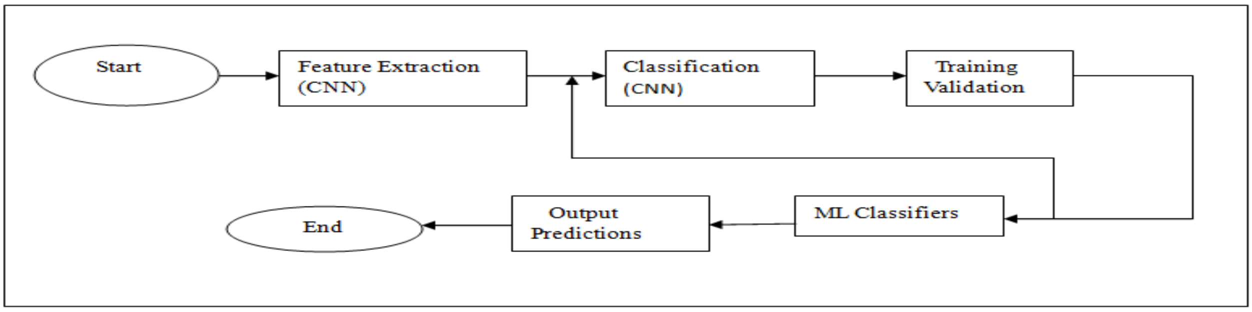

Figure 4: Flowchart of proposed method

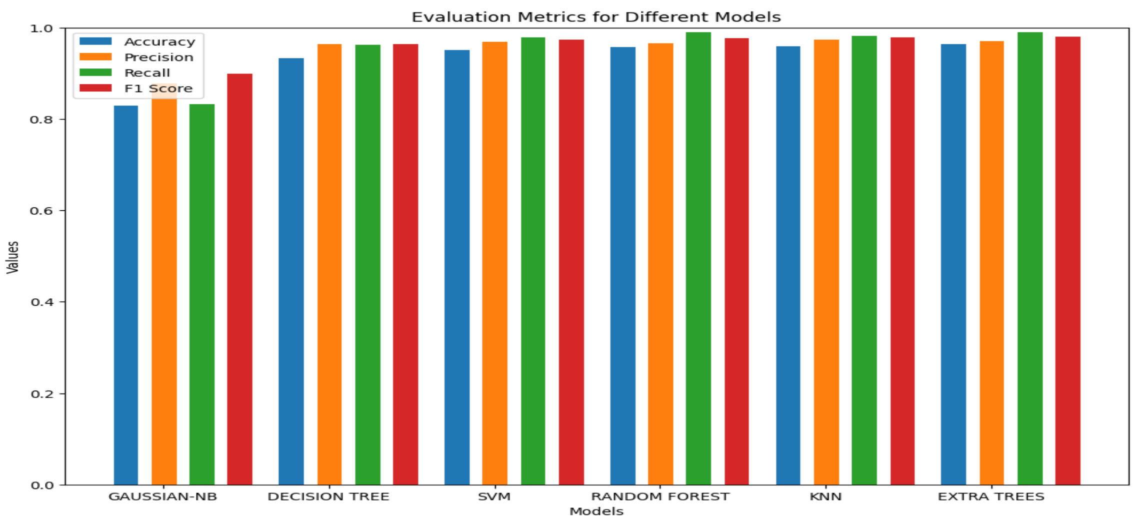

Figure 5: Performance of various ML classifiers

Once trained, the Extra Trees classifier predicts labels for the test dataset. The efficacy of the Extra Trees classifier is evaluated using assessment metrics like the confusion matrix and classification report. This combined methodology capitalizes on CNN's dual roles for feature extraction and classification, while the Extra Trees classifier contributes as the classification model. The complete methodology is given in Fig. 4.The various machine learning classifiers used in this model are SVM, Random Forest, Decision Tree, Gaussian-NB, KNN and Extra Trees. Out of all these mechanisms Extra Trees exhibits higher accuracy value. This setup synergizes the feature extraction and classification capabilities of the CNN model with the Extra Trees classifier, potentially leading to enhanced classification accuracy and overall performance on the test set.

From Fig. 4 it's evident that one approach involves utilizing the extracted features directly after the feature extraction step as input for the machine learning classifiers. Another method incorporates an intermediate step of showcasing training and validation graphs. In this method, the classification is applied subsequent to the feature extraction. The outputs obtained from the classification process serve as input for the classifier, leading to the final classification.

6.1 Assessment metrics

Evaluation metrics are essential tools for gauging the effectiveness of the proposed method, encompassing accuracy, precision, recall, and other factors. These metrics provide valuable insights for comprehensive assessment

Accuracy: It quantifies a classification model's correctness by comparing correct predictions to the total predictions

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \quad \text{……………………….. (1)}$$

Precision: It signifies true positives (TP) relative to the total of positive predictions (TP + FP):

$$\text{Precision} = \text{TP} \,/\, (\text{TP} + \text{FP}) \quad \text{…………………….… (2)}$$

Recall: It reflects the proportion of accurately classified positive samples among all actual positive samples:

$$\text{Recall} = \text{TP} \,/\, (\text{TP} + \text{FN}) \quad \text{…………………..……… .(3)}$$

F1-Score: It balances precision and recall for an accurate model evaluation:

$$\text{F1Score} = {}^{2 * (\text{Precision} * \text{Recall})}\!/\, ((\text{Precision} + \text{Recall})) \quad \text{……………………………………………. (4)}$$

TP: In the context of classification models, TP represents the number of correctly predicted positive instances.

TN: It represents the number of correctly predicted negative instances.

FP: It represents the number of incorrectly predicted positive instances.

FN: It represents the number of incorrectly predicted negative instances. The Kappa coefficient (Cohen's Kappa) gauges agreement between raters or classifiers assigning categorical labels. It ranges from negative to positive, indicating agreement levels like slight, fair, moderate, Substantial, or almost perfect.

Mean Average Precision (MAP) is computed by averaging the AP values across all queries. SLIC is an algorithm used for super pixel segmentation, which involves dividing an image into compact, perceptually meaningful regions or segments. Accuracy is computed from SLIC.

7 Results and discussion

Various Machine leaning algorithms such as SVM, Decision Tree, KNN, Random Forest, Gaussian-NB, and Extra Trees are implemented for classification. Fig. 5 depicts the performance for various algorithms in terms of accuracy, precision, f1 score and recall. Extra Trees shows higher values when compared with other algorithms. Table.1. shows the values of the various metrics.

Table1: Summary of various machine learning classifiers

Model	**Overall accuracy**	**Kappa**	**Precision**	**Recall**	**F1score**
Extra Trees	0.9635	0.9621	0.9705	0.9904	0.9804
SVM	0.9508	0.9482	0.9685	0.9784	0.9739
RF	0.9579	0.9561	0.9655	0.9897	0.9775
KNN	0.9589	0.9572	0.9740	0.9816	0.9778
DT	0.9332	0.9284	0.9646	0.9628	0.9637
G-NB	0.8288	0.7935	0.8780	0.8330	0.8997

Table 1 provides a performance comparison of different models on the classification task. The evaluation metrics include overall accuracy, which measures the proportion of correctly classified instances, And the Kappa coefficient, serves as a metric to gauge the level of agreement or reliability between two raters when categorizing items into distinct groups. Kappa between 0 to 1 indicate agreement that is better than chance, with superior values indicating stronger agreement.

Additionally, precision, recall, and F1 score are provided to evaluate the model's performance concerning class-specific metrics. Higher values of these metrics generally indicate better model performance. From Table 1 it is inferred that Extra Trees exhibits higher accuracy of 0.9635 when compared with all other machine learning algorithms. The overall accuracy measures the proportion of correctly classified instances, and a higher value indicates better performance in terms of the total number of correct predictions. According to [13] the obtained kappa coefficient of Extra Trees is 0.9621 which is stated that lies within the range. The results obtained from the trained models indicate the performance of the CNN-based feature extraction model and the Dense Neural Network classifier. The test loss and accuracy provide an overall assessment of the model's predictive capability on unseen data.

The confusion matrix reveals the model's performance for each class, identifying True Positives, True Negatives, False Positives, and False Negatives. The classification report presents metrics such as precision, recall, and F1-score giving insights into the model's performance across different classes. By analyzing these results, it is possible to evaluate the model's effectiveness, predict its strengths, and identify areas for improvement. The discussion of the results provides valuable insights into the model's performance, which can inform decision-making and potential applications in various domains.

The waveforms of CNN Extra Trees training and validation loss and accuracy are illustrated in Fig.6 and confusion matrix is shown in Fig.7.

7.1 Comparison with other studies

Comparing the outcomes of the proposed model with existing cases from the literature involves subjectivity. To facilitate this comparison, 13 recent studies are Extra Tree Techniques, as outlined in Table 2. Notably, the highest accuracy of 96.35% was achieved through the utilization of the CNN model coupled with the Extra Tree classifier.

7.2 Limitations and complexity of proposed model

The proposed method of utilizing a CNN for feature extraction and classification, followed by an Extra Trees classifier, offers a powerful fusion of deep learning and traditional machine learning techniques. However, this approach entails complexities and limitations. The intricate interplay between the CNN's learned features and the Extra Trees algorithm requires careful alignment and validation.

While the CNN's capacity to capture intricate patterns can be advantageous, potential challenges include hyper parameter tuning for both models, data availability for effective CNN training, and difficulties in interpreting CNN-derived features. Balancing these complexities and limitations is essential to harness the combined strengths of the two methods effectively.

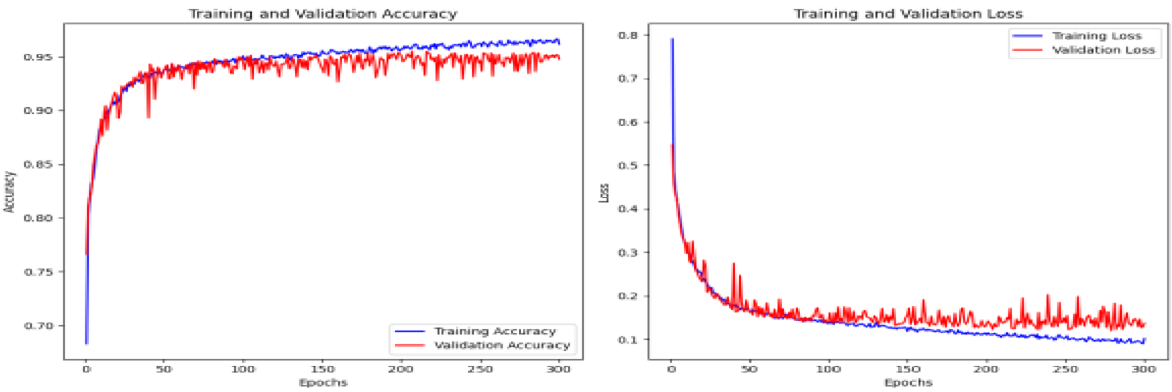

Figure 6: Wave forms of training, validation loss and accuracy of CNN Extra Tree

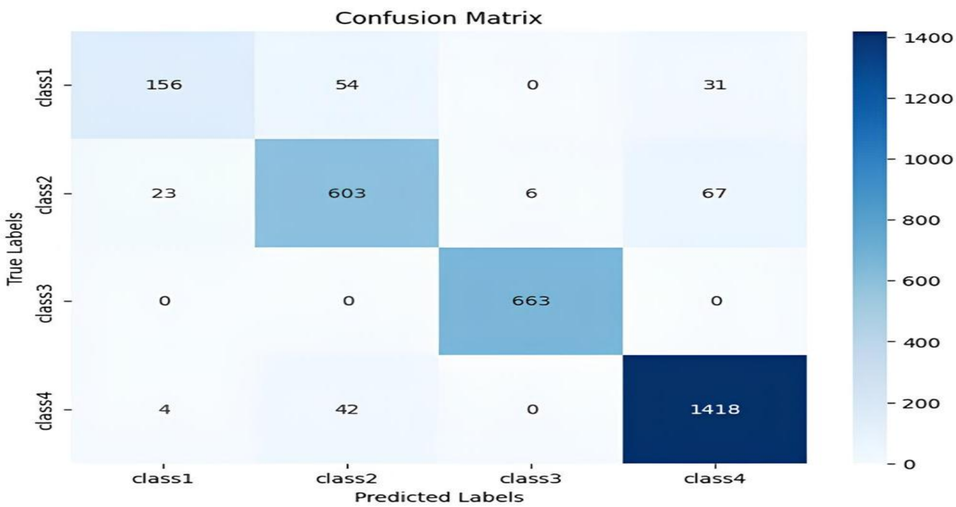

Figure 7: Confusion Matrix of CNN

Table 2: Comparison of proposed model with other studies from the literature

Model	Accuracy	Recall	F1- Score	Precision	Reference
Random Forest	82	93.3	92.1	-	[2]
Decision Trees	68	-	-	-	[4]
SVM	94	91	89	91	[6]
KNN	63	62	89	62	[6]
VGG16	92	92.1	52	92	[8]
SLIC-RF	91	99	91	100	[10]
Object-based	89	90	-	93.40	[11]
One-class	90	-	-	-	[13]
Single Shot Detector	84	80	78.5	81	[16]
SVM	66	-	-	-	[7]
RCNN	95	94.7	-	95.3	[18]
YOLO-V3	91	66	68	65	[17]
Relief-F	80	87.26	91.24	91.73	[19]
Extra Trees	96	99	98	97	Proposed method

8 Conclusion

The classifiers like Random Forest, Support Vector Machine, K-Nearest Neighbours, and Extra Trees are used in this paper. The proposed method of combining CNN for feature extraction, classification and Extra Trees as the classifier offers a promising approach for image classification and obtained an accuracy percentage of 0.9635. This method presents a versatile approach to image classification that merges the capabilities of deep learning and traditional machine learning. This strategy offers a promising solution for complex tasks, yet navigates challenges such as hyper parameter tuning, data availability, and interpretability. While demanding in terms of complexity, the model's potential to capture intricate patterns through the CNN's feature extraction and refine those using Extra Trees demonstrates its potential utility in tackling diverse classification problems. The Extra Tree classifier obtained an impressive accuracy of 96.35% along with an outstanding kappa coefficient of 96.21%.

Acknowledgement

I would like to extend deep sense of gratitude to the authorities of Acharya Nagarjuna University for the encouragement and support to do this work.

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