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Digital Image Object Detection with GLCM Multi-Degrees and Ensemble Learning

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Abstract

Object detection in digital images has been implemented in various fields. Object detection faces challenges, one of which is rotation problems, causing objects to become unknown. We need a method that can extract features that do not affect rotation and reliable ensemble-based classification. The proposal uses the GLCM-MD (Gray-Level Co-occurrence Matrix Multi-Degrees) extraction method with classification using K-Nearest Neighbours (K-NN) and Random Forest (RF) learning as well as Voting Ensemble (VE) from two single classifications. The main goal is to overcome the difficulty of detecting objects when the object experiences rotation which results in significant visualization variations. In this research, the GLCM method is used to produce features that are stable against rotation. Furthermore, classification methods such as K-Nearest Neighbours (KNN), Random Forest (RF), and KNN-RF fusion using the Voting ensemble method are evaluated to improve detection accuracy. The experimental results show that the use of multi-degrees and the use of ensemble voting at all degrees can increase the accuracy value, and the highest accuracy for extraction using multi-degrees is 95.95%. Based on test results which show that the use of features of various degrees and the ensemble voting method can increase accuracy for detecting objects experiencing rotation.

Keywords: *Object detection; object rotation; Gray-level Co-occurrence Matrix Multi-Degrees; Ensemble Voting*

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1. Introduction

Object detection is a digital image technology to recognize an object based on its features [1]. This technology has been implemented widely in various fields. In the health sector, disease diagnosis is based on medical image data. The field of object detection security for face recognition from surveillance system images [2]–[4]. The object detection process has its challenges, especially when an image object experiences rotation which is influenced by various factors [5]–[7]. Images that experience rotation will produce variations in visualization. Rotation of an image produces an orientation of the object in the image, resulting in significant variations in the object representation. Images from different angles of the same object can appear very different [8]. This becomes an obstacle in the detection process because the system has difficulty detecting the object. This problem causes a decrease in accuracy and errors in the classification process [9]. To increase the accuracy value for objects undergoing rotation, it is necessary to develop a model where the extraction section uses an orientation-based method. One of these methods is GLCM (Gray-Level Co-occurrence Matrix). The GLCM method utilizes the distribution of gray levels in the image, from one pixel to the gray levels of other adjacent pixels [10], [11]. The uniqueness of this method lies in its ability to extract these features from all variants and all orientation angles, thus allowing the formation of features that are constant or stable even if there are rotational changes in the image [12]–[14].

Extraction in GLCM uses contrast, correlation, energy, entropy, and homogeneity. The characteristics obtained from the extraction results need to be analyzed, one of

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which is by using classification. For example, research conducted by Nyasulu et al., (2023) explored the use of Gray Level Co-occurrence Matrix (GLCM) based texture characteristics such as ASM (Angular Second Moment), Correlation, Contrast, Dissimilarity, Energy, and Homogeneity for the classification of fungal diseases in leaf. tomato. Classification uses ANN (Artificial Neural Network), K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM). The result was that the ANN was superior, with an overall accuracy of 94% and an average score of 93.6% for Precision, 93.8% for Recall, and 93.8% for F1-score. These results demonstrate the great potential of the extracted texture features in classifying fungal diseases on tomato leaves.

The use of classification methods for detection such as in research conducted by Sulaiman et al., (2024) evaluated the use of hybrid machine learning models to measure phosphorus concentrations in hydroponic systems, machine learning techniques such as Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN) both individually and combined with ensemble methods (voting, bagging, and stacking), showing that the hybrid model increases prediction accuracy. In particular, the stacking model combines SVM, KNN, and RF with high accuracy with efficient computing time.

Apart from that, research conducted by Zhang et al., (2023) on Ensemble learning BRR-SVR-BPNN (Bayesian Ridge regression - backpropagation neural network - support vector regression) to reduce deviations in dimensional measurements using a monocular vision system in industrial environments. This algorithm integrates Bayesian Ridge Regression, Support Vector Regression, and Backpropagation Neural Network techniques. This research successfully shows that this algorithm is superior in deviation prediction compared to other methods, offering a robust and accurate solution to increase measurement precision in industrial applications.

In research conducted by Shehab & Kahraman, (2020) discusses improving the performance of the Extreme Learning Machine (ELM) through an ensemble approach that focuses on pruning and selecting weights.

Research conducted by Yuan et al., (2023) shows a feature selection algorithm called SSMI (combination of sinusoidal sequences and mutual information), which combines sinusoidal sequences and mutual information to overcome challenges in data classification in machine learning. SSMI is effective in removing distracting and redundant features from high-dimensional datasets. This algorithm has the advantages of flexibility and anti-redundancy and anti-interference capabilities, using phase adjustment in a sinusoidal sequence to select the number of key features. SSMI succeeded in reducing an average of 15 features from each dataset, increasing the average classification accuracy by 3% on the KNN classifier, and achieving high accuracy on the HBV(Hepatitis B Virus) and SDHR(hort-duration heavy rainfall) datasets. However, this method still has limitations, such as the inability to eliminate intermediate features with small differences and correlation analysis between variables. The next step is to improve this algorithm to further improve classification accuracy and efficiency.

Research by Islam et al., (2023) on an illegal access detection framework in the Industrial Internet of Things (IIoT) using a voting-based Ensemble Learning method. The framework uses Machine Learning (ML) techniques the latest and classics such as Histogram Gradient Boosting (HGB), CatBoost, and Random Forest (RF) are used, with CatBoost showing the highest accuracy of 99.85%, surpassing both HGB and RF. The system uses stochastic variations of ResNet50 and other models, outperforming other methods in the literature. Although automatic image orientation remains a challenge, especially in datasets with uncertain orientation.

Analysis using classification is a process for grouping or entering objects or data into predetermined categories based on their features or characteristics [21]. Machine learning in the object classification, process involves training an algorithm using data that has been labeled to recognize patterns[22]–[24]. Important features of objects are associated with appropriate labels. The goal is so that the algorithm can classify new objects accurately based on the features that have been learned from training data [25]. One classification method that is often used is K-Nearest Neighbours (K-NN) [26], [27].

This method uses the distance between the object to be classified and the existing training objects. Objects are classified based on many labels from their K nearest neighbours. The Random Forest classification method excels at handling large datasets and is resistant to overfitting. These methods build multiple decision trees during training, producing predictions based on averages [28], [29].

The contribution of this research is the integration of GLCM-MD extraction with VE-based classification methods [25], [30]. The use of GLCM-MD for feature extraction offers an advancement by accommodating changes in object orientation at all angles, ensuring that the extracted features remain stable and relevant to accurate object classification. This model combines a single classification of K-NN and RF in a VE framework, which not only improves detection accuracy but also offers a more robust solution to variations in the orientation of encountered objects.

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2. Research Methods

The digital image object detection model is shown in Figure 1. In this model the GLCM extraction process uses Multi Degree (MD) to obtain features (GLCM-MD), and uses a single classification of KNN and RF, to optimize the results by applying VE.

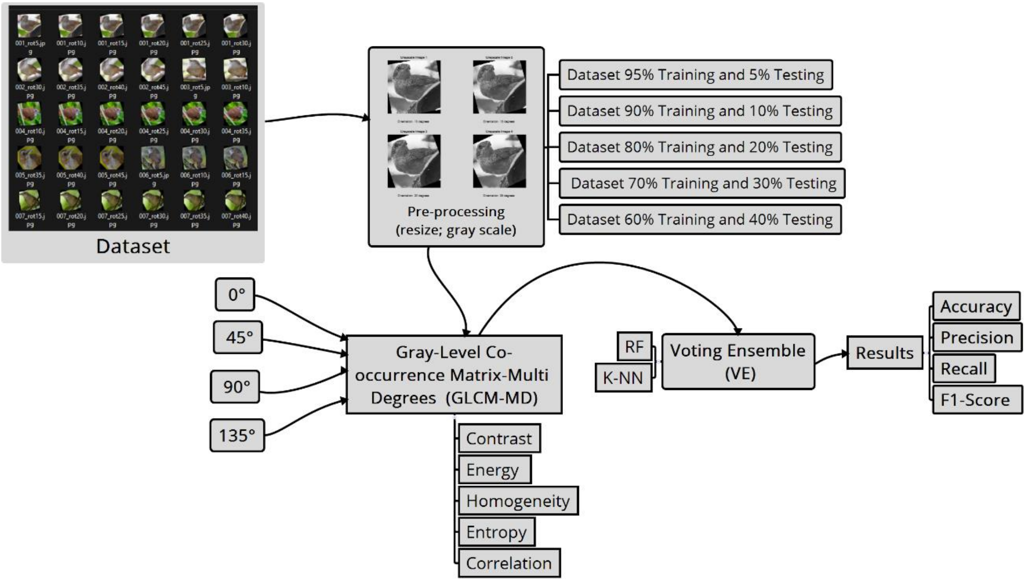

Figure 1 Model Classification Algorithm with Voting Ensemble and GLCM-MD

A dataset of 4,437 with details of 1,467 class1, 1,233 class2 and 1,737 class3 data samples is shown in Figure 2(a) sample class1, 2(b) sample class2, and 2(c) sample class3, Figure 2(d) object orientation in various angles .

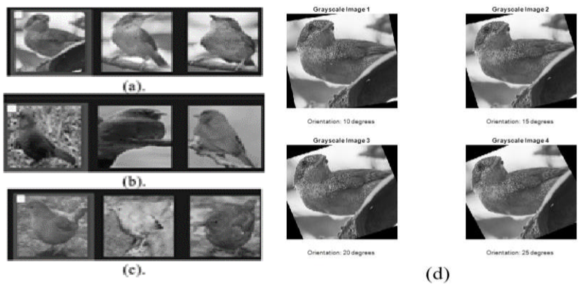

Figure 2. Image Object (a). class1 (b). class2 (c). class3 (d). objects in a grayscale image with orientation

Model testing uses training data with training variations ranging from 60% to 95% for each class, shown in Table 1.

Table 1 Training and Test Dataset Variants

No	Training Dataset	Test Dataset
1	95%	5%
2	90%	10%
3	80%	20%
5	70%	30%
6	60%	40%

The extraction method uses the Gray-Level Co-occurrence Matrix (GLCM) by using all spatial orientations or degrees (MD) in extracting texture features from digital images. The GLCM formula is shown in equation (1) to equation (5). [32], [33] images.

$$Energy = \sum_i \sum_j P(i,j)^2 \tag{1}$$

$$Contrast = \sum_i \sum_j (i-j)^2 * P(i,j) \tag{2}$$

$$Homogeneity = \sum_i \sum_j \frac{P(i,j)}{1+(i-j)^2} \tag{3}$$

$$Entropy = -\sum_i \sum_j P(i,j) * log\big(P(i,j)\big) \tag{4}$$

$$Correlation = \frac{\sum_i \sum_j [ij * P(i,j)] - \mu_x * \mu_y}{\sigma_x * \sigma_y} \tag{5}$$

Where for i and j is the index of the co-occurrence matrix. Meanwhile, P(i,j) is an element of the co-occurrence matrix at position (i,j). Next, for µx and µy, the average of the row and column weights in a co-occurrence matrix. The values σx and σy are the standard deviation of the row and column weights in a co-occurrence matrix..

These features include entropy, homogeneity, contrast, and energy. GLCM in analysis can use one of four degrees 0°, 45°, 90°, and 135° [8]. The proposed model uses GLCM Multi-Degrees (GLCM-MD) extraction so that the features obtained come from multi-domain extraction. Each feature in GLCM has different characteristics. Energy as in equation (1) measures the gray level in the image concentrated at the same value. High-energy images will show high energy

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concentrations at certain gray levels [34]. The contrast in Equation (2) analyses the gray level of a pixel and its neighbours in the image. A high contrast value means there is a difference between a pixel and its neighbours. Meanwhile, homogeneity in Equation (3) describes a uniform image in terms of gray level. A high homogeneity value will indicate a uniform or homogeneous gray level. Entropy in Equation (4) is one of the extracted features that measures the level of irregularity or texture complexity in the image. The higher the entropy value, the more complex and irregular the texture. Correlation as in Equation (5) assesses the linear relationship between intensity values of adjacent pixels in an image. Correlation measures how much changes in pixel values at one location relate to changes in adjacent pixel locations. Correlation values can range from -1 to 1, where values close to 1 indicate a strong and positive linear relationship, values close to -1 indicate a strong but negative relationship, and values close to 0 indicate no or very weak relationship.

Pseudocode Voting Ensemble

Inputs:
- Datasets (X,y)
- Number of neighbors (k) for KNN
- Number of trees (n_trees) for RF

Output:
- Class prediction (y_pred)

Process:
1. Divide the dataset into two parts: training data (X_train, y_train) and test data (X_test).
2. Initialize two models, namely KNN and RF.
3. Train the KNN model with training data:
   - For each data in X_train:
   - Find k-nearest neighbors based on k.
   - Calculate the class majority of the neighbors.
   - Set the majority class as the prediction for the data.
4. Train the RF model with training data:
   - Repeat n_trees times:
   - Randomly select a subset of training data with replacement (bootstrap).
   - Build the nth tree using the subset.
5. For each data in X_test:
   - Make predictions using the KNN model and RF model.
   - Save prediction results from both models.
6. Vote to select the majority class from the KNN and RF prediction results:
   - Count the number of votes for each class from the predicted results.
   - Select the class with the most votes as the ensemble prediction.
7. Output ensemble predictions as output.

The features extracted using GLCM-MD are classified using KNN and RF and the combined stages of the voting ensemble method are shown in Pseudocode Voting Ensemble.

The ensemble voting method implements the K-Nearest Neighbours (KNN) and Random Forest (RF) algorithms in predicting the class of data based on a given dataset [35]–[38]. In the first stage, the dataset is divided into two parts, namely training data (X-train, y-train) and test data (X-test). In the second stage the models, namely KNN and RF, are initialized [39]. The KNN model is trained with training data, for each data in Meanwhile, the RF model is trained with training data n-trees times using the bootstrap technique [40],[41].

The training results of the two single classification models were tested for predictions on the X-test data. Prediction results from KNN and RF are saved. In the next stage, the majority of classes are selected from the KNN and RF prediction results by counting the number of votes for each class from the prediction results, and the class with the highest number of votes is selected as the ensemble prediction. The ensemble prediction results then become the output of the pseudocode (Voting Ensemble).

3. Results and Discussions

Testing the detection model as shown in Figure 1, the stages are as follows, each dataset is resized, and grayscale pre-processed before being extracted with GLCM-MD. Testing with dataset variants Table 1. Testing using a single K-NN and RF classification model, the classification results are used in the ensemble voting model with pseudocode shown in Table 3. The test results for KNN are shown in Table 2.

Table 2. K-Nearest Neighbours (KNN) Model

Training Size	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
60%	83.10	84	81	82
65%	83.71	84	88	86
70%	85.05	84	83	83
75%	87.47	86	87	86
80%	88.39	89	84	87
85%	89.04	90	86	88
90%	90.32	90	92	91
95%	93.24	92	95	93

In Table 2, the evaluation for the KNN model shows the highest accuracy when the amount of training data is 95% with an accuracy of 93.24%, likewise the precision, recall and F1-score values show the best results.

Table 3. Random Forest (RF) Model

Training Size	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
60%	84.23	87	80	83
65%	85.90	82	93	87
70%	87.23	90	84	87
75%	88.37	89	84	87
80%	89.40	95	83	88
85%	89.64	92	85	89
90%	89.86	87	96	91
95%	91.89	93	90	92

Evaluation of the Random Forest (RF) model shown in Table 3, has a slightly lower accuracy than K-NN, namely 91.89 but still shows good performance with precision, recall and F1-score with high results. By using KNN and RF the classification results were improved using VE, the results showed an increase in accuracy of 93.69%, and high precision, recall, and F1 Score values are shown in Table 4.

Table 4. VE Model

Training Size	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
60%	84.34	81	89	84
65%	85.83	91	85	88
70%	86.78	81	91	86
75%	88.82	88	87	87
80%	90.76	87	92	90
85%	90.24	87	93	90
90%	91.44	95	91	93
95%	93.69	88	99	93

The next test uses different single degrees starting from 0°, 45°, 90°, 135° and multi-degrees (MD), the results are shown in Figure 3

Testing uses single GLCM degrees ranging from 0 to 135 degrees and combined (multi degrees). The classification method uses the K-Nearest Neighbours (KNN), Random Forest (RF) algorithm, and combining KNN-RF using the Voting ensemble method.

The results for extraction with 0 degrees, with an accuracy between 68.45% to 74.77%, RF has an accuracy of around 76.00% to 78.83%, and the Voting Ensemble method has an accuracy between 71.32% to 76.80%.

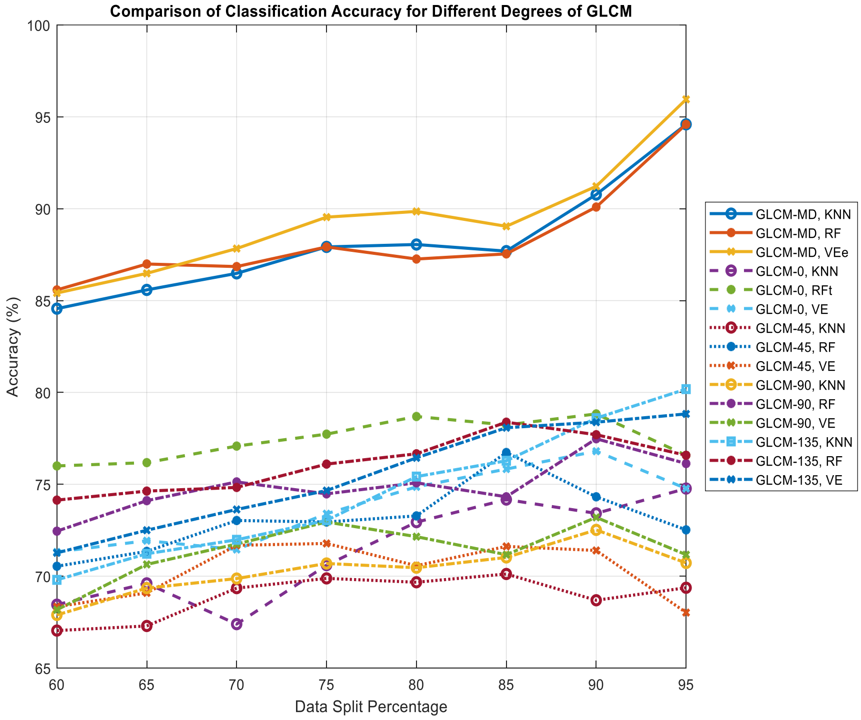

Figure 3. Testing using single-degree and multi-degree

45-degree GLCM extraction, KNN has an accuracy between 67.04% to 69.37%, RF has an accuracy ranging between 70.54% to 76.73%, and the Voting method achieves an accuracy between 68.34% to 71.78%. For the 90-degree GLCM feature, KNN produces an accuracy of around 67.89% to 72.52%, RF has an accuracy of between 72.45% to 77.48%, and the Voting method has an accuracy of between 68.17% to 73.20%. With 135-degree GLCM extraction, KNN achieves an accuracy between 69.80% to 80.18%, RF has an accuracy of around 74.14% to 78.83%, and the Voting method has an accuracy between 71.27% to 78.83%. Meanwhile, using multi degree GLCM (GLCM-MD), KNN produces an accuracy of around 84.56% to 94.59%, RF has an accuracy of between 85.58% to 94.59%, and the Voting method has an accuracy of between 85.41% to 95.95%. These results show increased accuracy using MD compared to using GLCM with a single degree.

4. Conclusion

Test results using the GLCM extraction method at various degrees and various classification methods, such as K-Nearest Neighbours (KNN), Random Forest (RF), and Voting Ensemble methods, reveal various findings. GLCM orientation has a significant effect on classification performance. The ensemble voting method tends to increase accuracy compared to a single KNN or RF, while the use of a combination of all orientations (multi degrees) produces the highest accuracy of up to 95.95%. These results show that adapting the GLCM method and orientation to suit the

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classification task and dataset is essential to achieve the best results in pattern recognition.

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