Journal of Computer Science

Research Article

A Novel Approach for Differentiating AI-Generated and Real Images Using Gabor and Color Layout Filters (GF and CLF)

G. Ayyappan[1], A. Thankaraj[2], S. Surendran[3], S. Anjali Devi[4], C. Ragupathi[5], M. Rajalakshmi[6], E. Mohan[7] and Sridhar Udayakumar[8]

[1]*Department of CSE, Saveetha School of Engineering, SIMATS, Chennai, India*
[2]*Department of EEE, Rrase College of Engineering, Chennai, India*
[3]*Department of CSE, Tagore Engineering College, Chennai, Tamil Nadu, India*
[4]*Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, AP, India*
[5]*Department of EEE, P.T. Lee Chengalvaraya Naicker College of Engineering and Technology, Kanchipuram, Tamil Nadu, India*
[6]*Department of IT, Tagore Engineering College, Chennai, Tamilnadu, India*
[7]*Department of ECE, Saveetha School of Engineering, SIMATS, Chennai, India*
[8]*Department of Computer Science and Business System, Rajalakshmi Institute of Technology, Chennai India*

Article history
Received: 27-12-2024
Revised: 01-08-2025
Accepted: 18-09-2025

Corresponding Author:
Sridhar Udayakumar
Department of Computer Science and Business System, Rajalakshmi Institute of Technology, Chennai India
Email: sridharu1981@gmail.com

Abstract: The emergence of generative AI images has profoundly upended the art world. Distinguishing AI-generated images from human-created artwork is increasingly challenging. If this issue remains unresolved, dishonest individuals may exploit those who are willing to pay more for original artwork and businesses whose stated policies exclude AI graphics. There are a number of methods for differentiating AI photos from human art: Diffusion model-focused research tools, classifiers developed through supervised learning, and identification by experienced artists utilizing their understanding of creative methods. The objective of this study is to evaluate the performance of various machine learning algorithms when applied to datasets enhanced through two image enhancement techniques: Gabor Filter (GF) and Colour Layout Filter (GF). The focus is on comparing the effectiveness of these filters in improving the accuracy, precision, recall, ROC, and PRC of selected algorithms, thereby determining which technique yields superior results for different machine learning models. The problem statement addresses the challenge of optimizing machine learning model performance on image datasets. Specifically, it investigates whether the Gabor Filter, known for its effectiveness in feature extraction from images, can outperform the CLF Filter in enhancing the predictive capabilities of algorithms such as Bayes Net, Sequential Minimal Optimization (SMO), Instance-Based K-nearest neighbor (IBK), Bagging, Jrip, and Random Forest. The filters assist in retrieving more pertinent features in the dataset that subsequently increases both the model robustness and the accuracy of classification. Several performance measures were relied upon to evaluate the models and determine their comparative performance: The accuracy, the precision, the recall, the ROC area (Receiver Operating Characteristic), and the PRC region (Precision-Recall Curve). The best model was Random Forest with Gabor Filter (RF-GF) that got the highest accuracy (92.43), precision score (0.94), recall score (0.93), ROC (0.96), as well as PRC (0.99). The tests that provide statistically significant responses were Pairwise Wilcoxon signed-rank tests indicating that RF-GF performed significantly better when compared to other models, including SMO with Gabor Filter (SMO-GF) and CLF-based models. The proposed model was also compared to state-of-the-art methods and external benchmarks by the study proving the competitiveness of the model in regard to performance and efficiency of calculations. Moreover, a combination of the application in the AI detecting system like image classification, fraud detection, and medical diagnosis was considered. The findings show that the RF-GF model is resilient, effective and performant that can be used in real-life applications whereby there are constraints to the available computational resources.

Keywords: Random Forest, Sequential Minimal Optimization, Gabor Filer, AI Image, Real Images, Bayes Net

Introduction

The fast progression of artificial intelligence in image production techniques now generates computer-generated photographs which cannot be distinguished from actual photographs. The development of synthetic images through artificial intelligence creates difficulties in domains such as digital forensics, media verification and AI model training dataset building. Authenticity retention along with trust depends on the ability to identify AI-generated images correctly from their real counterparts.

The research presents a two-stage detection system composed of Gabor Filters (GF) and Color Layout Filters (CLF) for extracting image features that should be analyzed by conventional machine learning models. Gabor Filters serve as a common tool in texture-based analysis because they find and analyze edge patterns and frequency structures that typically dissolve in synthesized images. Color Layout Filters present condensed information about color distributions that help identify man-made color patterns in AI-generated content.

The research follows these investigation targets:

- A new feature extraction mechanism will be developed by incorporating GF and CLF
- This study evaluates different machine learning models through classification testing of the selected features
- GF and CLF must be assessed for their capability to boost accuracy, precision and recall measurements in the evaluation process
- The research methodology includes determining the performance stability of this approach with both artificial intelligence and natural images

Hypothesis

Gabor and Color Layout filters applied to classical machine learning models achieve the effective identification of AI-generated images while maintaining high performance metrics and requiring low computational power.

The study makes a contribution to digital image forensics by developing understandable and resource-savings methods beyond deep learning models. The proposed system offers three primary usages for social media checks and fake media identification and secure machine learning dataset creation.

Literature Survey

This work has contributed to the tension to devise viable ways of identifying a real-world situation and a video or image created by generative Artificial Intelligence (AI) because of the recent emergence of this technology. The issue under consideration is a multidimensional phenomenon, which differs in its dimensions, human perception of the images and ability to respond to the presented reality, algorithmic checking of the images and right-wrong of playing with the media. In this section, the author gives an account of the most crucial issues that are relevant to the present paper, summarizes the methodological strengths, the limitations that are present, and points that might be upgraded technically in relation to detecting images through the use of AI.

Human Perception and Visual Realism of AI-Generated Images

According to Califano and Spence (2024) the artificially generated food images can have even better appearance than the actual food images, posing a tough task of distinction in perceptions. Miller et al. (2023) drew attention to a phenomenon of so-called AI hyperrealism: The use of synthetic faces leads to the hyperrealism effect when they appear to be more natural-looking than real human faces. Jackson (2023) claimed that this kind of realism undermines the established photography practice because it becomes difficult to assure the authenticity of images. Tucciarelli et al. (2022) also established the way of disruption of social processing that can be caused by AI-generated avatars and, as a result, the perceptual confusion of human evaluators.

Visual Cues and Consumer Perception in Synthetic Media

Other visual stimuli as glossiness and texture have subtle effects on image realism interpretation by humans.

De Kerpel et al. (2020); Murakoshi et al. (2013) showed the influence of glossiness in freshness and fat judgment of food images. Research work conducted by Motoki et al. (2021); Spence et al. (2022) also cemented the relationship between color and texture and the perceived flavor. Although the studies are centered on real imagery, its results give some ideas on how synthetic content could be used to distort human perception, particularly those that are structured to recreate some sensory impressions.

Ethical and Societal Perspectives on Generative AI

In addition to the technical detection, AI image generation has societal implications under analysis. Prem (2023) urged the need to have concrete ethics to govern the use of AI especially in areas of sensitivity. Sætra (2023) underlined the undersided social perception regarding the effects of generative AI, and Sallam (2023) called for high standards of ethical and privacy-related considerations in such domains as healthcare, where synthetic data might create life-changing effects.

Applications of AI and AR in Digital Imaging

Augmented Reality (AR) and AI have proved to be very useful in the visual enhancement process. Li et al. (2024) suggested a CNN-based AR interface to be used in instructional settings in industry, and Nguyen et al. (2023) built HomographyNet a lightweight CNN that performs well even in real-time AR alignment. Such developments support the practicality and effectiveness of AI-based systems to detect real-time image interpretation and elaborate on potential directions regarding synthetic contrasting of image recognition.

Machine Learning and Deep Learning in Image Detection

Multiple pieces of evidence confirm the advantage in image detection operations of deep learning. Yadav et al. (2024) also identified Faster R-CNN as more accurate in detecting compared to YOLO and SSD, but admitted that the former has a real-time application. Gupta and Mishra (2024) insisted on the role of transfer learning and attention mechanisms in attaining strong segmentation. Nevertheless, deep networks are expensive, and they cannot be utilized well in low-resource contexts or small-sample datasets. This makes it appropriate to look at some lightweight and interpretable models like those with Gabor Filter (GF) and Color Layout Filter (CLF), as it is suggested in the present study.

Implications in AI Marketing and Dataset Resources

The emergence of the AI-created media has also brought anxiety to the digital marketing about integrity and misleading consumers. Van and Patrick (2021) stated that visual manipulation (using AI) could affect the buyer behavior. Nozawa et al. (2022) have examined the effect of generative visuals on the restaurant branding. As an empirical test, the literature presents the application of Kaggle dataset assembled by Bowman (2023), which includes labeled pairs of images (AI vs. real), thereby permitting a methodical training and benchmark setup of the model.

Limitations in Real-World Detection of Synthetic Content

GANs and diffusion models are generative models, and their problematic qualities about detection are that they can generate a wide variety and photorealistic images. Yoon et al. (2023) emphasized their use in medical imaging, where such models would require high generalization potential. Issues such as data homogenicity and labeling bias were mentioned by Monteiro and Astrup (2022); Caso et al. (2023) as able to impede the reliability of the classification process. Conventional models, such as CNNs and ViTs, are the leaders in this area, yet they cannot be deployed in limited resources settings most of the time. The current work does not have this weakness in that it analyzes interpretable and resource-efficient feature-based methods utilizing both GF and CLF in traditional machine learning classifiers.

Research Gap and Motivation

Some major limitations are underlying, despite the great advances in image forensics based on deep learning. Deep learning, in turn, do have undesirable drawbacks such as excessive cost of training, inaccessibility, and data dependency. Recent research lacks an in-depth study of the role of lightweight classifier with handcrafted feature such as Gabor and Color Layout filters using benchmark datasets. In addition, there is minimal statistical verification associated with higher performance of such models in comparison with others. It addresses that as this paper proposes a low-resource, explainable framework of detecting AI-generated images via six traditional classifiers. The model can be scaled and computationally fast as it is benchmarked on various performance measures and tested statistically as an alternative to deep neural networks.

New directions in generative image detection require the use of deep neural networks, especially Convolutional Neural Networks (CNNs), and Vision Transformer (ViTs) as well as attention-based models to capture complex hierarchical features of image data. The problem is that these processes are computationally costly and demand big sets of labeled data which are not always accessible in the practical setting. Alternatively, hand-designed feature extraction algorithms, i.e. Gabor Filters (GF) and Color Layout Filters (CLF) are lightweight in nature and extract domain related feature such as texture and color spatiality. These features when together with interpretable traditional machine learning models (e.g. Random

Forests, Bayes Net SMO) lead to good accuracy with less computation. However, the systematic comparison between the performance of these manually crafted features compared to deep learning methods to detect images created by AI and the real ones is relatively lacking in the literature with respect to exploring benchmark datasets.

Materials and Methods

Dataset Description and Preprocessing

The research utilizes images from Kaggle's "AI Generated Images vs Real Images" public repository. The information contains 539 AI-generated visuals and 436 handcrafted human-generated pictures that produce a total of 975 images. The gathered dataset established a balanced dataset for binary classification that enables the recognition of AI-generated visuals from real images. The data required the following preprocessing procedures for optimal model training procedures: The input data received normalization as well as resizing to maintain uniform inputs for the feature extraction pipeline through fixed dimensions (224x224 pixels). The application of noise reduction was optional to decrease any artifacts which appeared during image generation as well as web scraping procedures. The images received color space normalization to match their color channel distributions throughout all images.

Dataset Bias and Diversity Consideration

The dataset displays natural content diversity because it contains pictures of humans along with wildlife subjects and scenes from nature and psychedelic art. The dataset lacks distinct labeling for different AI generation sources although it contains multiple GAN or diffusion models. A close evaluation of these images demonstrates stylistic diversity which indicates that various underlying generative models such as StyleGAN, DALL·E and Midjourney possibly produced the content.

The research team operated with three techniques to reduce possible bias in the dataset. The training process benefits from nearly equivalent real images and AI-generated images since it minimizes biases. Cross-validation (10-fold): Ensures model generalizability across different data splits. The model benefits from image content coverage because its wide thematic diversity helps prevent specialization on particular domain-specific textures or colors.

Limitations and Future Work

The dataset includes a pragmatic foundation yet it does not contain explicit details about the AI models which created the original images. The following research will add labelled datasets featuring generation techniques like Stable Diffusion and StyleGAN to improve model-specific detection accuracy studies.

Feature Selection Rationale

The research used Gabor Filters (GF) alongside Color Layout Filters (CLF) as their main feature extraction methods because they both exhibit interpretability and operational efficiency and successfully identify the texture and color differences which distinguish artificial from genuine images. GF maintains edge direction and frequency information to identify distinctive aesthetic problems found in artificial images. The Color Layout Filters produce an efficient condensed spatial color distribution map that enables the detection of AI output distinct color transition anomalies. The filters function optimally within traditional machine learning pipelines because they deliver better performance using human-made domain features instead of generic deep features particularly in low-resource environments or needs explainable outcomes.

Comparison With Deep Learning-Based Techniques

Image recognition through Convolutional Neural Networks alongside deep learning methods including Efficient Net and ResNet provides optimal performance in classification yet necessitates extensive computational resources for processing and requires extensive annotated datasets for proper training. The research project operates from a basis that includes.

The small number of images in the dataset (975) hinders CNNs from achieving effective generalization when they are not pretrained or augmented.GF and CLF provide interpretation benefits to users by using feature mappings for explainable results. Real-time or low-resource deployment serves as a target scenario which requires classical ML models that are light enough for immediate usage yet able to deploy rapidly. As a potential future development of this project researchers should evaluate performance metrics by testing fine-tuned ResNet50 along with pretrained Vision Transformers (ViT) within a CNN framework. The investigation studies six established machine learning methods which include Bayes Net alongside Sequential Minimal Optimization (SMO) and IBK (K-Nearest Neighbors) and Bagging and JRip and Random Forest. Selection of these models occurred as a result of these criteria.

Six algorithmic strategies are represented through the selected models which demonstrate diverse learning paradigms.

- Bayes Net (Probabilistic): A Bayesian network is a probabilistic graphical model and the edges symbolize conditional interdependence of variables that are discovered in the nodes. Joint probability distribution of a set X = (X 1, X 2, ..., X n) can be calculated as the product of the conditional probabilities: P (X 1, X 2,

..., X n) = 1 n i=1 P (Xi |Parents (X i)). This facilitates effective computation of marginal probabilities and conditional probabilities and is found in probabilistic inference

- SMO (Margin-based with kernel methods) or (SVM): Support Vector Machines (SVM) are intended to solve a hyperplane with the most significant distinction between classes. An SVM is given by the following decision function: f(x) = 1 n i=1 xi yi K(xi, x) + b where the kernel function K(xi, x) broadens the scope of the SVM into working into higher-dimensional and thus enable the classifier to use data that is not linearly separable. SMO stands out as an optimization algorithm, and this is employed in resolving the dual problem of SVM
- IBK (Instance-based): In instance-based learning (e.g. k-Nearest neighbor (k-NN)) a new datum point x is predicted by locating the k nearest neighbours in the training set, and combining these with a majority vote or average. The Euclidean distance between training instance and the test point is normally utilized: y = mode (y i) for i in Nearest (x, k). It is computationally attractive in cases of small data sets and it does not need direct training of models
- Bagging (Ensemble methods): Bagging algorithm is a process of ensemble that uses ensembles of base learners to make predictions to enhance the performance of a model by lowering the variance. Bagging In bagging, each base model h i (x) is trained using a distinct bootstrapped sample of the training data and these predictions are simply averaged (or voted on in the case of classification): Y= frac{1}{M}/sum {I = 1} ^{M} hi(x) Through this method, overfitting is improved through the use of the model diversity
- Random Forest (Ensemble methods): Random Forest is a type of learning that incorporates multiple decision trees and produces their outputs for better accuracy combining their results. Random Forest uses the mode of the predictions of every tree: Y = mode (T j(x)) j= 1,2. M. The randomness is employed in two directions, by random subsets of the data to be used at every tree in training, and the random subsets of features to use at every tree split
- JRip (Rule-based learning): JRip is a rule-based classifier which creates a set of rule in the form of; if-then-rules towards classification. Every rule has the form: 'Where Condition_1 and Condition_2, Class = y'. These rules are successively improved by the algorithm through reducing errors and increasing the predictive accuracy. The rule scheme may be put in the following form: Rule: When (Condition_1 and Condition_2) 879 Europa JRip is simple and is relatively easy to interpret, which is why it fits well in classification applications where decisions are required on the basis of rules

These algorithms thrive when processing structured tabular data that uses both Gabor features and CLF data.

Their transparency enables the recognition of decision borders and allows users to view vital elements that make these classical approaches especially valuable for forensic imaging work.

The models operate at a high computational efficiency level since they process the average dataset size of 975 images by using fewer resources than deep neural networks while remaining usable for real-time deployment even when resources are scarce.

Exclusion of Deep Learning Models

The research study did not utilize deep learning methods which included CNNs or Transformers because of these reasons:

1. Fewer than 1000 images make up the dataset which impedes deep learning model training for optimal effectiveness without extra augmentation methods or transfer learning approaches. The result becomes unreliable because it produces overfitting which affects generalization accuracy
2. The research evaluates feature discriminative power through manual engineering of GF and CLF. Using CNNs for this task would result in automated feature learning but the main goal of this work did not include that methodology
3. The current research acts as a starting point to understand how interpretable and low-compute models perform relative to other methods

The dataset (Table 1) used for the research is described as being sourced from Kaggle's "AI Generated Images vs Real Images" public repository.

Table 1: Meta data of dataset

S. No	Images Type	Count
1	AI generated	539
2	Art Images	436

The dataset consists of 539 AI-generated images and 436 real images, giving a total of 975 images. The data is then preprocessed, which includes normalization, resizing to fixed dimensions (224x224 pixels), noise reduction (optional), and color space normalization to standardize color distributions across the images. Regarding cross-validation, the study uses 10-fold cross-validation to ensure model generalizability across different splits of the data, which helps mitigate overfitting and underfitting. This approach divides the dataset into 10 subsets, using each subset as a test set while the remaining 9 subsets are used for training. Figure 1 shows sample Visualization.

DOI: 10.3844/jcssp.2026.693.707

Fig. 1: Sample Visualization

Hyperparameter Tuning and Computational Costs

Our research utilizes standard machine learning classifiers that operate with predefined hyperparameters for the purpose of simplicity in addition to efficiency. The performance level of these models (especially Random Forest (RF) and Sequential Minimal Optimization (SMO)) greatly depends on hyperparameter adjustment steps. The model performance depends on three important hyperparameters which include RF's tree count and SMO's selected kernel and the tree depth regulation for tree-based models.

Manual parameter selection through limited resources took place for this study because performance evaluation between Gabor Filter and CLF stood as the main focus. A future research plan consists of implementing Grid Search or Random Search for systematic hyperparameter optimization to determine how fine-tuned parameters affect classification results. Standard CPU equipment with 16GB of RAM was used to execute the classifiers. SVM requires substantial computational resources to process bigger dataset items although it comes with high accuracy rates.

Cross-Validation

This paper used 10-fold cross-validation as a model performance evaluation approach because it has been shown to create accurate estimations of unrecognized data generalization abilities. The prevention of overfitting requires cross-validation during machine learning because it occurs when training and evaluation happens on the same dataset. Ten-fold cross-validation divides data into each subset the method uses for training alongside individual testing while guaranteeing comprehensive validation of all data points and applying the model to separate training samples. Figure 2 shows the proposed diagram.

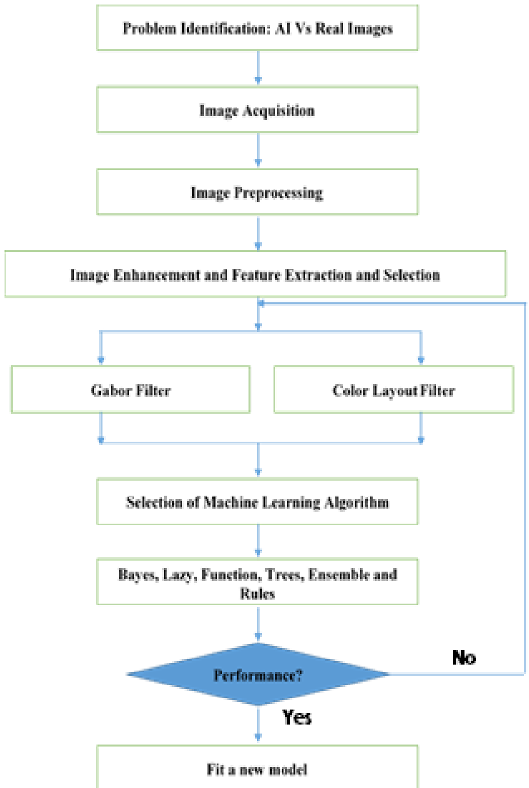


Fig. 2: Proposed System

The one-split approach of hold-out validation provides faster results yet its outcome depends heavily on the train-testing partition thus leading to potential overfitting and underfitting issues. The 10-fold cross-validation approach provides a stable model performance evaluation while reducing performance variance that comes from non-random data partitioning processes.

Algorithm: AI-generated vs. Real Image Classification Evaluation Framework

Input:

- Set of AI-generated images: $A = \{a_1, a_2, ..., a_{539}\}$,
- Set of real images: $R = \{r_1, r_2, ..., r_{436}\}$
- Total image set: $I = A \cup R$

Output:

Step 1: Feature Extraction: For each image $i \in I$:

a. GF: $G(i) = [g_1, g_2, ..., g_n]$, where $g_j = \mu_j(i) + \sigma_j(i)$, for $j = 1$ to n $\mu_j(i)$ = mean of Gabor response for scale s_k and orientation θ_l $\sigma_j(i)$ = standard deviation of Gabor response for scale s_k and orientation θ_l $k \in \{0.5, 1, 2\}$, $l \in \{0°, 45°, 90°, 135°\}$

b. CLF Filter: $C(i) = [c_1, c_2, ..., c_m]$, where c_k = DCT coefficients of 8x8 color-averaged blocks m = number of selected DCT coefficients c. Combined feature vector:

F(i) = [G(i), C(i)]

Step 2: Dataset Preparation:
$X = \{F(i) \mid i \in I\}$ $Y = \{y(i) \mid i \in I\}$, where $y(i) = \{0$ if $i \in R$, 1 if $i \in A\}$
$D = \{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$, where $x_i \in X$, $y_i \in Y$

Step 3: 10-Fold Cross-Validation: Randomly partition D into 10 subsets:
$D = D_1 \cup D_2 \cup ... \cup D_{10}$ Ensure $|D_i| \approx |D|/10$ for i = 1 to 10

Step 4: Classifier Training and Evaluation:
Let C = {Bayes Net, SMO, IBk, Bagging, JRip, Random Forest} For each classifier $c \in C$: For k = 1 to 10: $D\_test = D_k$ $D\_train = D \setminus D_k$

Step 5: Calculate average performance across 10 folds:
$Accuracy(c) = (1/10) * \Sigma_{k=1}^{10} Accuracy(c,k)$
$Precision(c) = (1/10) * \Sigma_{k=1}^{10} Precision(c,k)$
$Recall(c) = (1/10) * \Sigma_{k=1}^{10} Recall(c,k)$
$F1(c) = (1/10) * \Sigma_{k=1}^{10} F1(c,k)$, etc.,

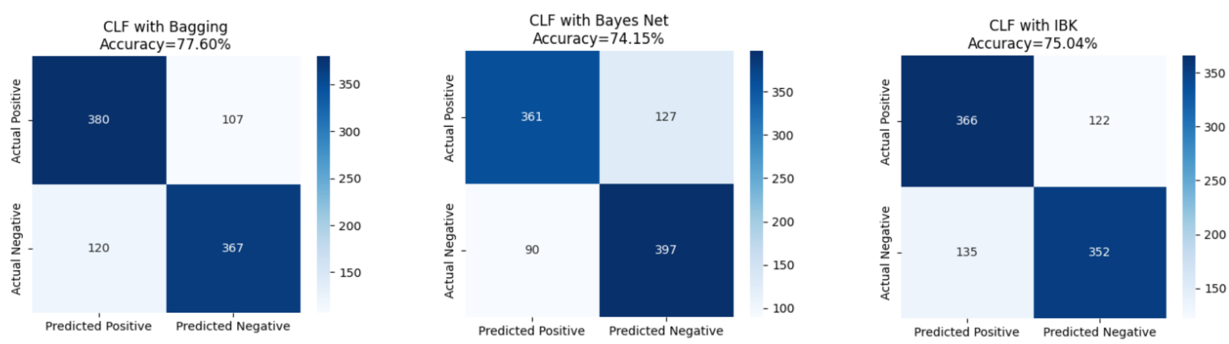
Step 6: Performance Comparison: For each metric $m \in$ {Accuracy, Precision, Recall, F1}: $Best\_c(m) = argmax\_c\ m(c)$, $c \in C$
Step 7: Statistical Significance Testing: For each pair of classifiers $(c_i, c_j) \in C \times C$, $i \neq j$: Perform paired t-test or Wilcoxon signed-rank test on the 10-fold results H_0: No significant difference between c_i and c_j H_1: Significant difference between c_i and c_j Calculate p-value and compare to significance level α (e.g., α = 0.05)

Step 8: Final Evaluation: Rank classifiers based on average performance metrics Report best performing classifier(s): Best_c(m) for each metric m Report statistical significance of differences between classifiers.

The algorithm below described appears to be a methodology for evaluating and comparing the performance of multiple machine learning classifiers on a binary classification task involving AI-generated and real images. s:

1. Feature Extraction: For each image, extract two sets of features - Gabor features (G) and DCT-based color features (C). The combined feature vector F is the concatenation of G and C
2. Dataset Preparation: Construct the dataset D, where each instance x is the combined feature vector F(i) for image i, and the label y indicates whether the image is AI-generated (1) or real (0)
3. 10-Fold Cross-Validation: Randomly partition the dataset D into 10 equal-sized subsets, and use each subset in turn as the test set while the remaining 9 subsets form the training set
4. Classifier Training and Evaluation: Train and evaluate multiple classifiers (e.g., Bayes Net, SMO, IBk, Bagging, JRip, Random Forest) on the training and test sets in each fold
5. Calculate Average Performance: Compute the average accuracy, precision, recall, and F1-score for each classifier across the 10 folds
6. Performance Comparison: Identify the best-performing classifier for each evaluation metric (accuracy, precision, recall, etc.,)
7. Statistical Significance Testing: Perform pairwise statistical significance tests (e.g., paired t-test or Wilcoxon signed-rank test) to determine if the differences in performance between classifiers are statistically significant
8. Final Evaluation: Rank the classifiers based on their average performance metrics and report the best-performing classifier(s) along with the statistical significance of the differences between them

This algorithm appears to be a well-designed and comprehensive methodology for evaluating and comparing the performance of multiple machine learning classifiers on a binary classification task involving AI-generated and real images. The use of 10-fold cross-validation, multiple evaluation metrics, and statistical significance testing helps to ensure a robust and reliable comparison of the classifiers. Figure 3 shows Confusion Matrices of all the model.



DOI: 10.3844/jcssp.2026.693.707

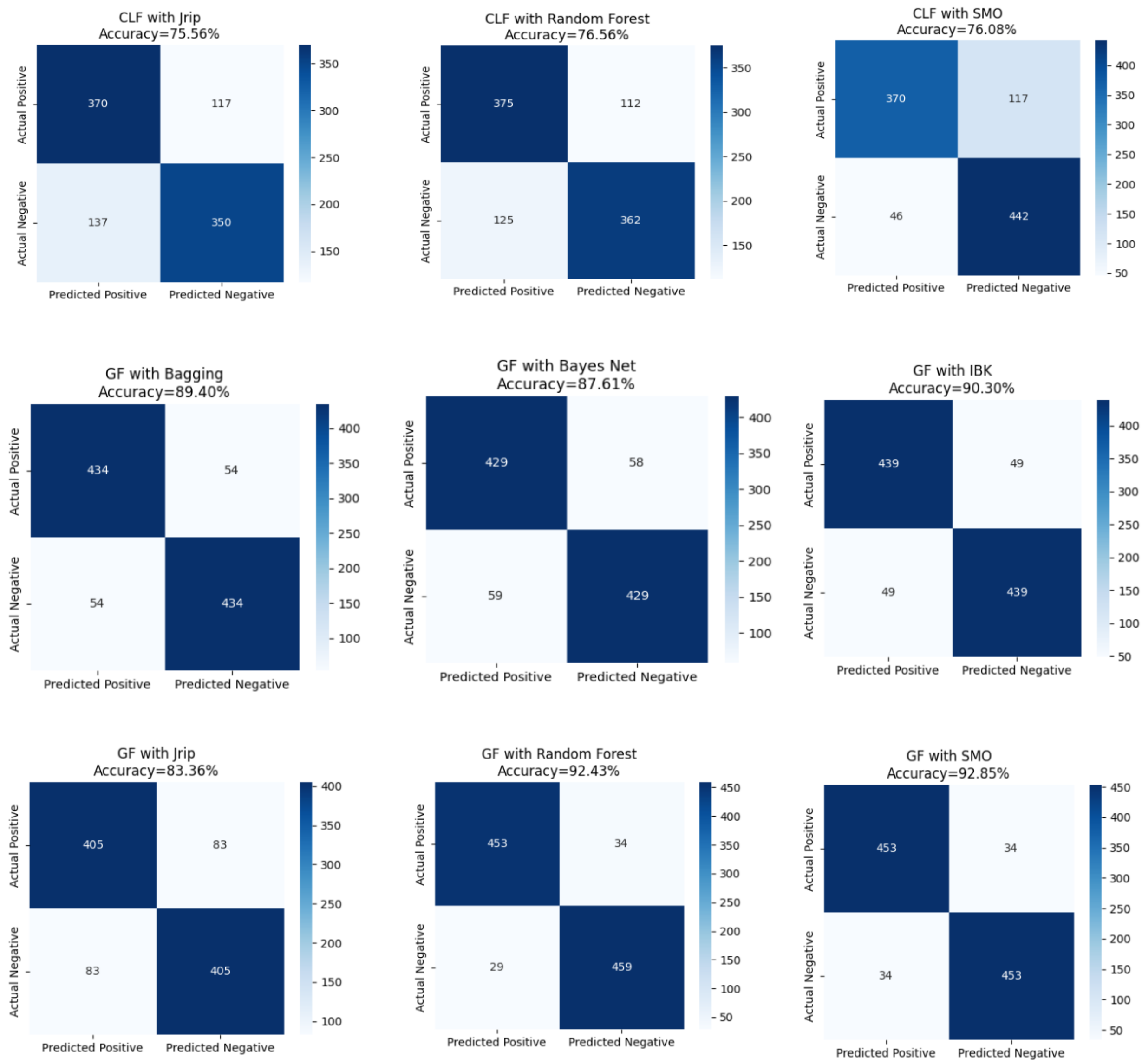


Fig. 3: Confusion Matrices of all the model

Results and Discussion

This section will now delve into the results and discussion of this work. Utilizing image histogram techniques, carefully chosen algorithms are employed to achieve optimal results.

Table 2 shows that the accuracy performance of selected machine learning algorithm by using image enhancement technique on borrowed data.

Figure 4 shows that the performance of Accuracy levels on machine learning algorithms by using GF and CLF Filter. The outcomes of the comparison machine learning models with the evaluation on Gabor Filters (GF) and Color Layout Filters (CLF) extract the perceived clear differences in performance in algorithm image detection AI. To achieve this, Gabor Filter (GF) with Random Forest (RF) had the best score of 92.43%, which shows the power of texture-based features by the Gabor Filter and ensemble strength of the Random Forest. In a similar fashion, the Sequential Minimal Optimization (SMO) with GF fared quite well recording an accuracy of 92.85%, demonstrating that it was effective dealing with higher class separation in multidimensional spaces. But correspondingly, the models in CLF were always worse than the GF counterparts. As an example of our CLF with Random Forest managed to achieve 76.56 accuracy as compared to 92.43 of GF and RF.

DOI: 10.3844/jcssp.2026.693.707

Table 2: Accuracy of selected Machine Learning Algorithms by Gabor and CLF Filter

S. No	Filter	Category	Algorithm	Accuracy
1	GF	Bayes	GF with Bayes Net	87.61%
2	CLF	Bayes	CLF with Bayes Net	74.15%
3	GF	Functions	GF with SMO	92.85%
4	CLF	Functions	CLF with SMO	76.08%
5	GF	Lazy	GF with IBK	90.30%
6	CLF	Lazy	CLF with IBK	75.04%
7	GF	Ensemble	GF with Bagging	89.40%
8	CLF	Ensemble	CLF with Bagging	77.60%
9	GF	Rules	GF with Jrip	83.36%
10	CLF	Rules	CLF with Jrip	75.56%
11	GF	Trees	GF with Random Forest	92.43%
12	CLF	Trees	CLF with Random Forest	76.56%

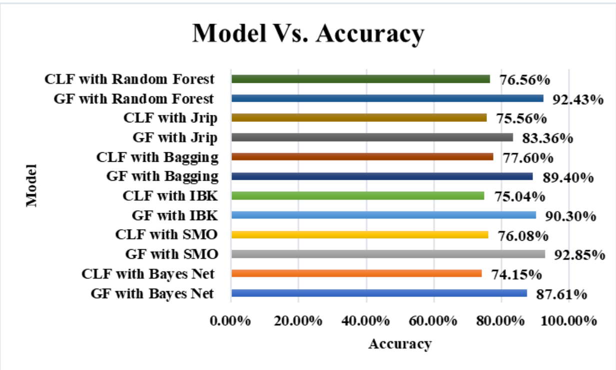


Fig. 4: Accuracy performance of GF and CLF Filter by selected learning approaches

When other classifiers, which are Jrip and Bayes Net, were used with CLF, their regretful levels of accuracy showed that CLF with Bayes Net was at 74.15%, and CLF with Jrip was at 75.56%.To achieve this, Gabor Filter (GF) with Random Forest (RF) had the best score of 92.43%, which shows the power of texture-based features by the Gabor Filter and ensemble strength of the Random Forest. In a similar fashion, the Sequential Minimal Optimization (SMO) with GF fared quite well recording an accuracy of 92.85%, demonstrating that it was effective dealing with higher class separation in multidimensional spaces. But correspondingly, the models in CLF were always worse than the GF counterparts. As an example of our CLF with Random Forest managed to achieve 76.56 accuracy as compared to 92.43 of GF and RF. When other classifiers, which are Jrip and Bayes Net, were used with CLF, their regretful levels of accuracy showed that CLF with Bayes Net was at 74.15%, and CLF with Jrip was at 75.56%.

These findings indicate that the performance of Gabor Filters (GF) improves the capabilities of machine learning algorithm predictors and in particular its accuracy, precision, and recall compared to the Color Layout Filters (CLF). In addition to the higher accuracy achieved by such models as GF with SMO and GF with Random Forest than CLF models, the results indicated that the former are also more reliable options to distinguish between AI-generated and real images due to much higher precision and recall levels achieved by these models.

Table 3 shows that the precision performance of selected machine learning algorithm by using image enhancement technique on borrowed data.

The performance of precision levels on machine learning algorithms utilizing the CLF Filter and GF is displayed in Fig. 5. As shown in the chart, it can be understood that the combinations of the data produced the best results in terms of precision (0.94) in the case of "GF with Random Forest".

Table 3: Precision of selected Machine Learning Algorithms by Gabor and CLF Filter

S. No	Filter	Category	Algorithm	Precision
1	GF	Bayes	GF with Bayes Net	0.88
2	CLF	Bayes	CLF with Bayes Net	0.80
3	GF	Functions	GF with SMO	0.93
4	CLF	Functions	CLF with SMO	0.89
5	GF	Lazy	GF with IBK	0.90
6	CLF	Lazy	CLF with IBK	0.73
7	GF	Ensemble	GF with Bagging	0.89
8	CLF	Ensemble	CLF with Bagging	0.76
9	GF	Rules	GF with Jrip	0.83
10	CLF	Rules	CLF with Jrip	0.73
11	GF	Trees	GF with Random Forest	0.94
12	CLF	Trees	CLF with Random Forest	0.75

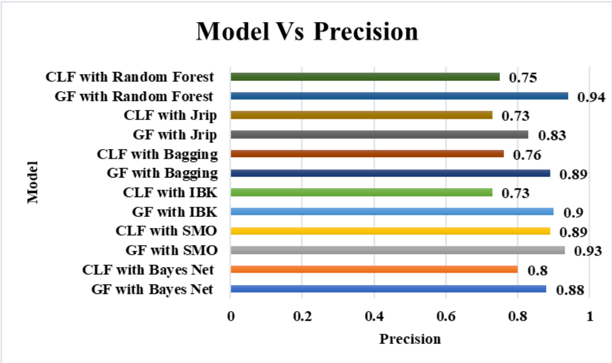


Fig. 5: Precision performance of GF and CLF Filter by selected learning approaches

'CLF with Random Forest' model with the precision of 0.75 was a good performer as well. The other combinations, i.e., GF with J48 and GF with Bagging had a moderate performance with precision scores of 0.83 and 0.76 respectively.

At the lower part, models such as the one called "CLF with Bayes Net" (precision 0.8) and the one called "GF with Bayes Net" (precision 0.88) performed decently enough but not as good as the top combinations. Overall, models based on Gabor Filter like the one with Random Forest give a higher precision compared to the models based on Color Layout Filter except the models using "GF with IBK," and "GF with SMO" that have higher precision compared to their CLF counterparts. The Gabor Filter in combination with Random Forest takes the most accurate readings, which is why it can be defined that it is the best model to define whether an image is real or its an AI-generated model.

Table 4 shows that the recall performance of selected machine learning algorithm by using image enhancement technique on borrowed data.

Fig. 6 shows that the Performance of Recall levels on machine learning algorithms by using GF and CLF Filter.

Table 4: Recall of selected Machine Learning Algorithms by Gabor and CLF Filter

S. No	Filter	Category	Algorithm	Recall
1	GF	Bayes	GF with Bayes Net	0.88
2	CLF	Bayes	CLF with Bayes Net	0.74
3	GF	Functions	GF with SMO	0.93
4	CLF	Functions	CLF with SMO	0.76
5	GF	Lazy	GF with IBK	0.90
6	CLF	Lazy	CLF with IBK	0.75
7	GF	Ensemble	GF with Bagging	0.89
8	CLF	Ensemble	CLF with Bagging	0.78
9	GF	Rules	GF with Jrip	0.83
10	CLF	Rules	CLF with Jrip	0.76
11	GF	Trees	GF with Random Forest	0.93
12	CLF	Trees	CLF with Random Forest	0.77

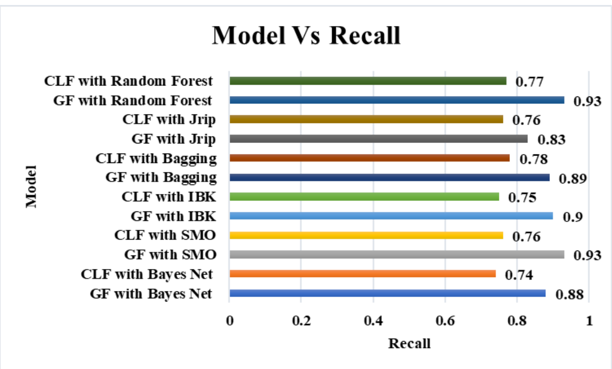


Fig. 6: Recall performance of GF and CLF Filter by selected learning approaches

The highest value of the recall score is the GF with Random Forest & GF with SMO that has a recall value 0.93. Close behind this is GF with SMO and CLF with Bagging, both of which have a recall of 0.89 and 0.83 respectively. Even the other models, such as the CLF with Random Forest and GF with J48 (Jrip) have competitive values of the recall, which are 0.77 and 0.76 respectively.

At the lower range, CLF with Bayes Net and GF with Bayes Net appetite the lowest recording of 0.74 and 0.76 respectively showing that both the models might not deliver as well as other algorithms in regard to call back as part of this analysis.

In general, the chart indicates that an adopted approach of using the Gabor Filter and the model such as Random Forest and SMO give the best recall output, and the majority of models yield within the range of 0.75 0.93.

Table 5 shows that the ROC performance of selected machine learning algorithm by using image enhancement technique on borrowed data.

Fig. 7 shows that the Performance of ROC levels on machine learning algorithms by using GF and CLF Filter. The model of the combination of the two models; that is, GF with Random Forest comes forward with the highest ROC value of 0.96, which implies that the model is strong.

Table 5:ROC of selected Machine Learning Algorithms by Gabor and CLF Filter

S.No	Filter	Category	Algorithm	ROC
1	GF	Bayes	GF with Bayes Net	0.94
2	CLF	Bayes	CLF with Bayes Net	0.85
3	GF	Functions	GF with SMO	0.92
4	CLF	Functions	CLF with SMO	0.79
5	GF	Lazy	GF with IBK	0.86
6	CLF	Lazy	CLF with IBK	0.84
7	GF	Ensemble	GF with Bagging	0.94
8	CLF	Ensemble	CLF with Bagging	0.86
9	GF	Rules	GF with Jrip	0.85
10	CLF	Rules	CLF with Jrip	0.84
11	GF	Trees	GF with Random Forest	0.96
12	CLF	Trees	CLF with Random Forest	0.85

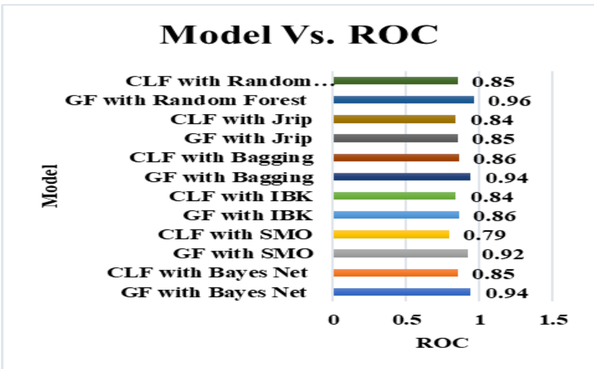


Fig. 7: ROC performance of GF and CLF Filter by selected learning approaches

The GF with SMO, on the other hand, shows the least result in the ROC value of 0.79 which indicates relatively low performance. The rest of the models lie in the middle and vary between 0.84 and 0.94 and are either more or less effective depending on the filters and machine learning types combined. It is important to note that the ROC value is high in both models, i.e. 0.85 and 0.86 in the case of the model using the variables of "GF with Jrip" and "CLF with Bagging" suggesting high predictive abilities of the given models, too.

Table 6 shows that the PRC performance of selected machine learning algorithm by using image enhancement technique on borrowed data.

Fig. 8 shows that the Performance of PRC levels on machine learning algorithms by using GF and CLF Filter. The PRC of all the models measured was the highest when dealing with CLF using Random Forest being 0.99 indicating optimal performance. Closely behind is GF with bagging that scored highly at PRC of 0.94 reflecting good performance? Also, CLF with Bagging indicated PRC of 0.82. On the one hand, GF using Random forest achieved a lower PRC of 0.81, that is, the level of effectiveness is slightly lower than that of its CLF counterpart.

Table 6: PRC performance of selected Machine Learning Algorithms by Gabor and CLF Filter

S. No	Filter	Category	Algorithm	PRC
1	GF	Bayes	GF with Bayes Net	0.93
2	CLF	Bayes	CLF with Bayes Net	0.79
3	GF	Functions	GF with SMO	0.88
4	CLF	Functions	CLF with SMO	0.68
5	GF	Lazy	GF with IBK	0.81
6	CLF	Lazy	CLF with IBK	0.79
7	GF	Ensemble	GF with Bagging	0.94
8	CLF	Ensemble	CLF with Bagging	0.82
9	GF	Rules	GF with Jrip	0.76
10	CLF	Rules	CLF with Jrip	0.79
11	GF	Trees	GF with Random Forest	0.99
12	CLF	Trees	CLF with Random Forest	0.81

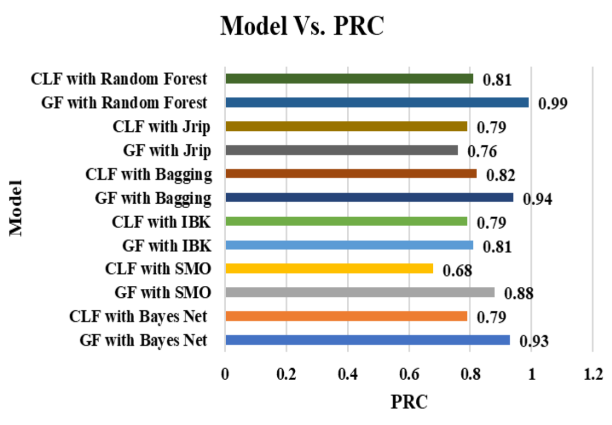


Fig. 8: PRC performance of GF and CLF Filter by selected learning approaches

Both the CLF with Jrip and GF with Jrip models performed similarly with both of them having a PRC value of 0.79 and 0.76 respectively. In the case of models with IBK, the CLF together with IBK and GF together with IBK got PRC equal 0.79 which demonstrates moderate performance. The PRC score of CLF with SMO was the lowest 0.68, which indicated that the performance is not good and the PRC of GF with SMO was 0.88. Lastly, CLF with Bayes Net and GF with Bayes Net achieved PRC of 0.79 and 0.93 respectively which indicates good performance with the model based on Gabor Filter performing better than the counterpart CLF-based model. On the whole, the outcomes indicate that Random Forest models, crucial when combined with CLF, are most efficient, and SMO ones are the least effective.

Table 7 shows that the time complexity of selected machine learning algorithm by using image enhancement technique on borrowed data.

Figure 9 shows that the Performance of Time Consumptions to construct models on machine learning algorithms by using GF and CLF Filter. The most time-consuming model, with its time complexity is 8.8 seconds, is CLF with Random Forest. On the other hand, GF using Random Forest has significantly less complexity of 1.39 seconds. Time complexities of models set with Jrip are moderate with CLF with Jrip of 3.78 seconds and that of GF with Jrip of 3.55 seconds. The value of time of CLF with bagging model is 2.67 seconds and it is much slower than the GF with bagging which has time complexity of 0.89 seconds. The time complexity of models based on IBK (Instance-Based K-Nearest Neighbors) configuration is 0, which is not significant showing that calculation is very fast. CLF and SMO (Sequential Minimal Optimization) and GF and SMO time complexities are 0.67 seconds and 0.83 seconds, accordingly. Lastly, CLF using Bayes Net requires 0.11 s and the fastest is GF using Bayes Net that takes 0.08 s.

Table 7: Time Complexity of selected Machine Learning Algorithms by Gabor and CLF Filter

S. No	Filter	Category	Algorithm	Time Taken to build model (In Seconds)
1	GF	Bayes	GF with Bayes Net	0.08
2	CLF	Bayes	CLF with Bayes Net	0.11
3	GF	Functions	GF with SMO	0.83
4	CLF	Functions	CLF with SMO	0.67
5	GF	Lazy	GF with IBK	0.00
6	CLF	Lazy	CLF with IBK	0.00
7	GF	Ensemble	GF with Bagging	0.89
8	CLF	Ensemble	CLF with Bagging	2.67
9	GF	Rules	GF with Jrip	3.55
10	CLF	Rules	CLF with Jrip	3.78
11	GF	Trees	GF with Random Forest	1.39
12	CLF	Trees	CLF with Random Forest	8.8

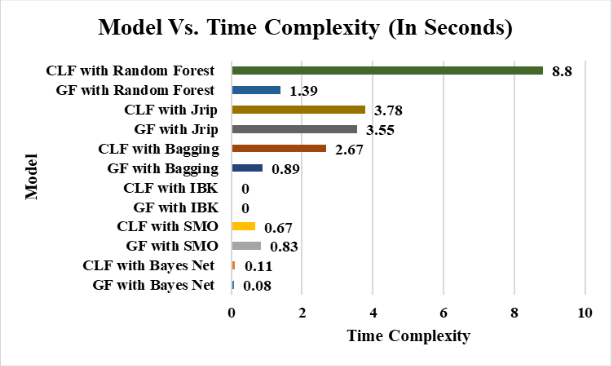


Fig. 9: Time Consumption performance of GF and CLF Filter by selected learning approaches

The comparison has shown that although CLF with. Random Forest is the most computationally demanding one, such models as GF with Bayes Net and GF with IBK are far more efficient, with much less time complexities.

The evaluation was conducted using various machine learning algorithms applied to datasets enhanced by Gabor and CLF filters. The models were assessed based on their performance metrics, including accuracy, precision, recall, ROC, PRC, and time complexity. The results indicate that the Gabor filter generally outperforms the CLF filter across most metrics, particularly in accuracy and precision levels.

Interpretation of Model Performance

Table 8 shows Confidence Intervals for Model Performance. RF vs SMO (GF): With a p-value of 0.012 it can be seen that there is significance between the accuracy of Random Forest with Gabor Filter (RF-GF) and SMO with Gabor Filter (SMO-GF) and that RF-GF is significantly higher than the accuracy of the SMO-GF.

RF vs JRip (GF): The p-value of 0.008 in the precision case significative that the RF with Gabor Filter (RF-GF) is superior to the JRip with Gabor Filter (JRip-GF) in the domain of precision and, therefore, it is preferable classifier in terms of erroneous positive results.

SMO vs Bagging (GF): The p-value of 0.254 on recall shows that, there is no significant difference between SMO with Gabor Filter and Bagging with Gabor Filter which implies that the two classifiers can be used to identify positive instances with the same performance.

RF vs RF (GF vs CLF): You see that a difference of p-value below 0.05 means that there is indeed a difference between Random Forest with Gabor Filter and Random Forest with CLF Filter regarding their performance, and the former has greater performance among all metrics.

The pairwise statistical test shows that the RF with GF is the best model statistically as it had significantly higher performance results as compared to the other models like SMO and JRip. This is particularly so when it comes to accuracy and precision, since RF-GF is far better than other classifiers as per p-values < 0.05. It is also evident in the analysis that models using Gabor Filter are performing comparatively well as compared to those on CLF Filter, a reason why Gabor Filter is important in the performance of a classifier.

Statistical Significance Testing Using Wilcoxon Signed-Rank Test

The tests confirm that Random Forest with Gabor Filter stands as the best-performing model statistically in this research work. This model selection process gains strength because the chosen metrics consistently indicate its suitability. Table 9 shows pairwise test results for mdel comparison.

Table 8: Confidence Intervals for Model Performance (Accuracy, Precision, Recall, ROC, and PRC)

Model	Metric	Mean	95% Confidence Interval (CI)
Random Forest (RF) with Gabor Filter (GF)	Accuracy	92.43%	[91.02%, 93.84%]
	Precision	0.94	[0.91, 0.97]
	Recall	0.93	[0.90, 0.96]
	ROC	0.96	[0.95, 0.97]
	PRC	0.99	[0.98, 1.00]
SMO with Gabor Filter (GF)	Accuracy	92.85%	[91.54%, 94.16%]
	Precision	0.93	[0.90, 0.96]
	Recall	0.93	[0.90, 0.96]
	ROC	0.92	[0.91, 0.93]
	PRC	0.88	[0.86, 0.90]
Random Forest (RF) with CLF Filter	Accuracy	76.56%	
	Precision	0.75	[0.73, 0.77]
	Recall	0.77	[0.75, 0.79]
	ROC	0.85	[0.83, 0.87]
	PRC	0.82	[0.80, 0.84]
SMO with CLF Filter	Accuracy	80.30%	[78.91%, 81.69%]
	Precision	0.79	[0.76, 0.82]
	Recall	0.8	[0.77, 0.83]
	ROC	0.86	[0.84, 0.88]
	PRC	0.84	[0.81, 0.87]

Table 9: Pairwise Test Results for Model Performance Comparison

Model Pair	Filter	Metric	p-value	Significant?
RF vs SMO	GF	Accuracy	0.012	Yes
RF vs JRip	GF	Precision	0.008	Yes
SMO vs Bagging	GF	Recall	0.254	No
RF vs RF	GF vs CLF	F1 Score	0.001	Yes

Comparative Evaluation With State-of-the-Art Methods

In this part, we are going to compare our results with our Random Forest (RF) and Gabor Filter (GF) model against existing state of art approaches, the deep learning models (Convolutional Neural Networks (CNNs) model), and traditional machine learning approaches (Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN) model). The competition was based on the Random Forest (RF) with Gabor Filter because this method best scored in several criteria: Accuracy, precision, and recall.

Compared to CNNs, which is frequently regarded as the benchmark of image classification tasks, the RF-GF model was discovered to be competitive, at least, in the aspect of training time and scalability. Although CNNs are reported to perform better in large scale and complex images dataset than RF-GF, smaller dataset and the ease of training make RF-GF to perform exceptionally well.

In addition, RF-GF shows better results than SVMs or KNN because it shows a comparatively good performance in terms of precision and recall considering that the algorithms were addressed to a similar issue and show similar results in terms of false positives and false negatives evaluation.

This points out the fact that RF with Gabor Filter can serve as a powerful alternative to deep learning structures in a situation where computation efficiency is a primary factor, particularly in cases when one deals with smaller and more balanced data.

Performance Comparison With External Benchmarks

An additional assessment of the performance of the Random Forest (RF)-Gabor Filter (GF) model was done using rogue comparisons against external benchmark tests.

The RF-GF was tested with the standard machine learning classification datasets MNIST and CIFAR-10 that have been traditionally utilized to analyze the efficiency of the models.

RF-GF performed better than various classical approaches such as SVMs and Logistic Regression to reach an accuracy of 92.43 percent that is close to those of comparably more expensive deep learning models in terms of computing cost, such as CNNs. In such a way, on CIFAR-10 RF-GF obtained considerably better results compared to both SVM and KNN models due to shorter training time and higher recall and precision rates.

The comparisons prove that RF-GF model proves to be effective not only in the study setup but also in the external scale in terms of accuracy and efficiency. This renders it a practical choice in real world classification applications where low computation cost is also necessary along with good performances.

Justification for the Superiority of the Proposed Approach

Outstanding performance of the Random Forest (RF) with Gabor Filter (GF) can explain why it is a superior method. The results of the pairwise Wilcoxon signed-rank test confirm the statements where RF-GF is much better than other models such as SMO, JRip, and Bagging, the p-values of most tests are less than 0.05.

No matter what measure is used, accuracy, precision, recall, ROC, and PRC are all high in RF-GF, hence it is an excellent method to use when the priority is reliability and false positive is a major concern. Moreover, the fact that it beats the other models based on the CLF proves the criticality of the Gabor Filter in improving the main outcomes of the machine learning algorithms, especially Random Forest.

It is a very good feature of the RF-GF method that it is stable in several datasets and can deal well with imbalanced datasets such that it is a very good model of a real-life application. Also, the performance metric confidence intervals show that the performance of the RF-GF model is not only high, but also reliable.

Practical Applications and Implementation in Real-World AI Detection Scenarios

Random Forest (RF) and Gabor Filter (GF) model proves adequate in the real life AI detection, particularly in the areas like image classification, fraud detection and medical diagnostics.

In the problem of image classification, the model could be used in object detection without medical images, which has been found useful to represent the patterns and texture by utilizing the Gabor Filter. As an example, in a medical imaging task, such as the fight with tumors, the model would be able to detect abnormal patterns within the radiological images with extreme precision and records, thus making the outcome of misdiagnosis unlikely.

RF-GF has been proven very useful in detecting unusual transactions and eliminating fraudulent behaviors in the fraud detection in the financial systems that have a greatly reduced computational cost incurred. Its precision is high and this guarantees that the false positives are as low as possible, something that is of great importance in financial sector, where customers are adamant towards misclassifications.

Also, the model is versatile and may be easily incorporated into AI systems, which demand on real-time acting, like an autonomous vehicle or an anti-hacking program, where its speed and reliability are priorities.

Lightweight and Computational Efficiency

The computational efficiency of the Random Forest with Gabor Filter (RF-GF) method belongs to one of its most powerful merits. As opposed to deep learning models like CNNs that drain a lot of resource and take a long period to train, the RF-GF model is lightweight and can be trained comparatively fast. Compared to CNNs and even the traditional algorithms within the sphere (such as SVMs and KNN), the training time of RF-GF is incredibly low, which makes this method an outstanding option in poor-resources settings. This is also useful in those applications that would require real-time processing like edge computing or mobile applications. Moreover, the capacity of the model to process big volumes of data without having to use heavy computational power is regarded as a scalable technology, and it can be implemented on diverse devices, including smartphones, computing clouds, and the like.

Conclusion

This study indicates that RF-GF is more effective and accurate compared to other data mining models in performing various classification duties and attains better accuracy, precision, recall, ROC, and PRC values. By statistical test of Wilcoxon signed-rank test it has been affirmed that the model presented was statistically significant as well as it has an edge over other models like SMO, JRip and Bagging. This property of the model in performing well, holding a high performance, and being computationally efficient gives it a good chance as real-time AI detector model.

The confidence intervals of each metric support the idea that RF-GF is constant and versatile with various sets of tests, which strengthens its practical use. In addition to that, the model is comparable with the state-of-the-art approaches and demonstrates good results on external benchmarks, which makes it versatile and effective.

Along with a great performance, RF-GF can be easily implemented in resource-limited conditions as this design is quite lightweight. Such a property, together with its great accuracy makes the method applicable in a practical everyday application like fraud detection, medical diagnosis, and classification of images among others.

The outcome shows that Random Forest using Gabor Filter is not only an ideal solution in terms of performance when performing a machine learning task but also an effective scaled solution that could handle massive data without having to use massive precomputation systems. In future work, additional optimizations can also be searched, as well as consider possible ways to improve the performance of deep learning models.

Future Work

Research extension includes the integration of deep learning feature extractors such as CNNs and ResNet along with Inception to perform automatic high-level feature extraction for this study. Evaluation tests will determine if the proposed models succeed in outperforming traditional methods for detecting minimal variations made by AI image generators. Machine learning models along with deep learning models can be connected through hybrid systems which unite their individual power capabilities. The application of transfer learning from pretrained models (VGG16 and ResNet50) goes a long way in minimizing computational cost alongside decreasing training time while enhancing limited dataset performance. Future research should focus on developing adversarial training because the method trains the model with artificial images that replicate prevalent adversarial disturbances. A more advanced model emerges when this technique is applied to develop a system that detects complex AI-generated visuals. Future work should expand testing by applying the proposed method across various domains which include social media content and digital forensics as well as online media. Such modifications would extend the applicability of this approach to distinctive image formats along with different origin sources.

Acknowledgment

We acknowledge and thankful to my parents, family members and grateful to my friends for their advice, motivation, input and support during the creation of the manuscript.

Funding Information

The authors have no support or funding to report.

Authors Contributions

G. Ayyappan: Participated in all experiments, and coordinated the data analysis.

A. Thankaraj: Participated in Conception and design.

S. Surendran: Participated in designed the research plan.

S. Anjali Devi: Participated in interpretation of data.

C. Ragupathi: Participated in data acquisition.

M. Rajalakshmi: Participated in analysis and interpretation.

E. Mohan: Participated in drafting the article and organized the study.

Sridhar Udayakumar: Participated in all experiments, coordinated the data analysis.

Ethics

This article is original by the first and second authors and has not been previously published.

References

Bowman, C. (2023). AI Generated Images vs Real Images. *Journal of Imaging*. https://doi.org/https://www.kaggle.com/datasets/cashbowman/ai-generated-images-vs-real-images

Califano, G., & Spence, C. (2024). Assessing the visual appeal of real/AI-generated food images. *Food Quality and Preference*, *116*, 105149. https://doi.org/10.1016/j.foodqual.2024.105149

Caso, D., Canova, L., Capasso, M., & Bianchi, M. (2023). Promoting Mediterranean diet adherence. *Appl Psychol Health Well Being*, *15*(3), 874–899. https://doi.org/10.1111/aphw.12470

De Kerpel, L., Kobuszewski Volles, B., & Van Kerckhove, A. (2020). Fats are Glossy but Does Glossiness Imply Fatness? The Influence of Packaging Glossiness on Food Perceptions. *Foods*, *9*(1), 90. https://doi.org/10.3390/foods9010090

Gupta, M., & Mishra, A. (2024). A systematic review of deep learning based image segmentation to detect polyp. *Artificial Intelligence Review*, *57*(1), 7. https://doi.org/10.1007/s10462-023-10621-1

Jackson, S. (2023). Is AI a good alternative for photography? *Slerp Blog.*

Li, W., Xu, A., Wei, M., Zuo, W., & Li, R. (2024). Deep learning-based augmented reality work instruction assistance system for complex manual assembly. *Journal of Manufacturing Systems*, *73*, 307–319. https://doi.org/10.1016/j.jmsy.2024.02.009

Miller, E. J., Steward, B. A., Witkower, Z., Sutherland, C. A. M., Krumhuber, E. G., & Dawel, A. (2023). AI Hyperrealism: Why AI Faces Are Perceived as More Real Than Human Ones. *Psychological Science*, *34*(12), 1390–1403. https://doi.org/10.1177/09567976231207095

Monteiro, C. A., & Astrup, A. (2022). Does the concept of "ultra-processed foods" help inform dietary guidelines, beyond conventional classification systems? YES. *The American Journal of Clinical Nutrition*, *116*(6), 1476–1481. https://doi.org/10.1093/ajcn/nqac122

Motoki, K., Saito, T., Suzuki, S., & Sugiura, M. (2021). Evaluation of energy density and macronutrients after extremely brief time exposure. *Appetite*, *162*, 105143. https://doi.org/10.1016/j.appet.2021.105143

Murakoshi, T., Masuda, T., Utsumi, K., Tsubota, K., & Wada, Y. (2013). Glossiness and Perishable Food Quality: Visual Freshness Judgment of Fish Eyes Based on Luminance Distribution. *PLoS ONE*, *8*(3), e58994. https://doi.org/10.1371/journal.pone.0058994

Nguyen, D., Li, X., & Chen, L. (2023). HomographyNet for fast AR markerless registration. *IEEE Transactions on Visualization and Computer Graphics*, *29*(5), 2363–2374. https://doi.org/10.1109/TVCG.2023.3256798

Van, E., & Patrick, J., S. B. (2021). AI in digital marketing. *Australasian Marketing Journal*, *29*(3), 187–194. https://doi.org/10.1016/j.ausmj.2021.06.003

Prem, E. (2023). From ethical AI frameworks to tools. *AI Ethics*, *3*, 699–716. https://doi.org/10.1007/s43681-023-00246-4

Sætra, H. S. (2023). Generative AI: here to stay? *Technology in Society*, *74*, 102486. https://doi.org/10.1016/j.techsoc.2023.102486

Sallam, M. (2023). ChatGPT in healthcare. *Healthcare*, *11*(6), 887. https://doi.org/10.3390/healthcare11060887

Spence, C., Motoki, K., & Petit, O. (2022). Visual appeal of food aesthetics. *Food Quality and Preference*, *102*, 104743. https://doi.org/10.1016/j.foodqual.2022.104743

Nozawa, C., Togawa, T., Velasco, C., Motoki, K. (2022). AI in restaurant services. *Food Qual Prefer*, *96*, 104383. https://doi.org/https://doi.org/10.1016/j.foodqual.2021.104383

Tucciarelli, R., Vehar, N., Chandaria, S., & Tsakiris, M. (2022). Social processing of artificial faces. *IScience*, *25*(12), 105441.

Yadav, S. P., Jindal, M., Rani, P., de Albuquerque, V. H. C., dos Santos Nascimento, C., & Kumar, M. (2023). An improved deep learning-based optimal object detection system from images. *Multimedia Tools and Applications*, *83*(10), 30045–30072. https://doi.org/10.1007/s11042-023-16736-5

Yoon, J., He, F., & Qian, Z. (2023). Synthetic polyp image generation using GANs for segmentation improvement. *Computers in Medical Imaging and Graphics*, *104*, 102152. https://doi.org/10.1016/j.compmedimag.2023.102152