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Deep Learning Approaches for Synthetic Images of Pharmaceutical Drugs and Vitamin Products Analysis

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***Abstract*—Drug labels and packaging inserts play a critical role throughout the pharmaceutical supply chain, from manufacturing and distribution to final consumption. The images of drug labels (also called display panels) can be used to detect illegal, counterfeit, unapproved or potentially harmful pharmaceutical products. But the manual inspection and verification process can be tedious and cumbersome, which demands for automatic and intelligent identification systems. In this research work, a machine learning-based framework is proposed for image analysis of pharmaceutical drugs and vitamins using the National Library of Medicine (NLM) Pill Image Dataset. Pharmaceutical images were extracted to train, validate and test a Random Forest (RF) classifier to distinguish pharmaceutical products. Accuracy, precision, recall and F1 score were evaluated to assess the proposed model. The experimental results showed that the RF model was able to give an accuracy (ACC) of 98.5%, precision (PRE) of 99.9%, recall (REC) of 98.5% and F1-score (F1) of 98.9%. Moreover, the comparison between the proposed RF model and deep learning models such as ResNet-50, CNN and YOLOv5s showed that the RF model achieved better classification ACC. The results show the success of machine learning approaches to automate drug and vitamin recognition, which is a solution that can be used for medication identification, counterfeit drugs detection, and healthcare decision-support applications.**

***Keywords*—Imaging, Image Analysis, Machine Learning, Drug Discovery, High-Throughput Screening, High-Content Analysis.**

I. INTRODUCTION

The rapid expansion of biomedical research has led to an unprecedented availability of biomedical and pharmaceutical data across multiple domains, including clinical records, experimental studies, ethnically diverse population datasets, and large-scale drug-related repositories. However, concerns remain regarding the proper transmission, integration, and utilization of this data to extract meaningful and actionable knowledge[1][2]. In the pharmaceutical sector, drug discovery and development remain highly complex processes that are both time-consuming and extremely costly, often constrained by multiple regulatory and experimental formalities that slow down innovation and increase financial burden [3].

Drug development is further complicated by several scientific and operational challenges, especially in identifying safe and effective drug candidates. A major limitation is the presence of unfavorable ADMET (Absorption, Distribution, Metabolism, Excretion, and Toxicity) properties, which frequently lead to late-stage failure of promising compounds in the drug development pipeline. Additionally, issues such as off-target effects, low efficacy, and toxicity risks continue to reduce the success rate of drug discovery[4][5]. To address these challenges, researchers increasingly utilize synthetic images of pharmaceutical drugs for early-stage screening, improving the robustness of predictive models and supporting more reliable evaluation of drug behavior [6][7].

Another critical aspect of pharmaceutical systems is drug safety, control, and distribution, where synthetic images of pharmaceutical drugs and synthetic images of vitamin products play a significant role in modern computational analysis. Medications can cause unintended side effects ranging from mild to severe conditions, making it essential to understand their safety profiles for informed decision-making[8] Furthermore, the presence of counterfeit, illegal, and unapproved drugs poses serious risks to public health[9]. In this context, synthetic images of pharmaceutical drugs are widely used in reference-based verification systems, enabling faster identification of suspicious samples through comparison with historical datasets [10].

In recent years, artificial intelligence (AI) has significantly transformed drug discovery and pharmaceutical image analysis through the integration of synthetic images of pharmaceutical drugs and synthetic images of vitamin products[11][12][13][14]. DL and ML techniques, including supervised, unsupervised, and reinforcement learning methods, have improved traditional cheminformatics, bioinformatics, and pharmacoinformatic approaches. These approaches leverage large-scale biomedical data together with synthetic images of pharmaceutical drugs and synthetic images of vitamin products to improve dataset diversity, reduce overfitting, and enhance model generalization. As a result, ML/DL-based systems have demonstrated improved predictive ACC and efficiency, accelerating drug identification, strengthening pharmaceutical classification,

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and advancing computer-aided drug design and analysis [15][16].

A. Motivation and Contribution

Motivation for this study is the growing demand for precise and automatic identification of pharmaceutical drugs and vitamin products to enhance patient safety and minimize medicine errors. The possibility of inaccurate drug identification exists due to the fact that manual drug recognition is typically laborious, time-consuming, and vulnerable to human mistake, particularly when dealing with comparable medicines. Intelligent image-based categorization systems capable of accurately and consistently identifying pharmaceutical goods are now within reach, thanks to advancements in computer vision and ML. Therefore, this study primarily aims to examine how well ML approaches work when applied to the analysis of pharmaceutical and vitamin images for the purposes of automated medication identification and healthcare decision making. The work in this research has the following important contributions:

Developed an automated pharmaceutical drug and vitamin image analysis framework using ML techniques for accurate medication identification.Utilized the NLM Pill Image Dataset containing diverse pill images to build and evaluate the classification system.Proposed a classification model using RF using image features for the recognition of pharmaceutical drugs and vitamin products.Supported healthcare providers in lowering medication errors and increasing patient safety by demonstrating the efficacy of ML for automated drug identification.Provided a reliable decision-support solution that can be extended to pharmaceutical product verification, counterfeit drug detection, and healthcare informatics applications.

B. Justification and Novelty

Automated and trustworthy medication identification systems are in high demand to enhance patient safety and decrease medication-related mistakes due to the fast expansion of vitamin goods and pharmaceutical drug varieties. For clever computer-based picture classification, the time-consuming, costly, and error-prone manual identification methods just don't cut it. The unique contribution of this research is the creation of a framework for the analysis of pharmaceutical medication and vitamin images using a RF classifier and the NLM Pill Image Dataset. In contrast to the existing work that primarily relies on DL models, this study demonstrates the efficacy of an ensemble ML approach in accurately classifying pharmaceutical images. The suggested framework is powerful, efficient, and scalable to easily recognize the drug and support health decisions automatically.

C. Organization of the Paper

The paper is structured as follows. The section II provides a literature review of previous research in the field. Section III delves into the discussion of the suggested approach and architecture. Section IV discusses the outcomes and comparisons, provides a full account of the experimental context, and details the results. The last section of the paper is Section V, which is the conclusion.

II. LITERATURE REVIEW

A thorough review and analysis of major research studies on Pharmaceutical Drug and Vitamin Image Analysis was carried out to get inputs and improve the design of this study.

G. Sunil et al. (2026) This study details the automated categorization of medicine and vitamin classes that include Alaxon, Bactidol, Bioflu, Bioguesic, Dayzinc, Daclogen, Fish Oil, Kremil S, Medicol, and Neozap using a high-performance DL system that is built on fine-tuned ResNet50. The sample is sourced from Kaggle and includes synthetic data photos that mimic the actual package differences. The suggested approach enhances feature extraction and generalization through pre-processing, data augmentation, and transfer learning. Comparing the model to benchmarks like VGG16, InceptionV3, MobileNetV2, DenseNet121, and EfficientNetB3 reveals its resilience and stability at 98% overall ACC. The assessment was conducted using PRE, REC, F1, confusion matrix, training, and validation analysis [17].

Basheeruddin et al. (2025) examine the function of AI in the pharmaceutical industry, with attention to essential methods such DL, virtual screening, target identification, PRE medicine, and NLP. The results of a meta-analysis including 12 trials showed that the ACC of drug-target interaction prediction was 0.57 (95% CI: 0.38-0.76). Included in the discussion are performance indicators such as MSE, ROC, and ACC. The heterogeneity, interpretability, and ethical implications of the data certainly affect pharmaceutical innovation going forward, even though XAI, multi-omics data, and real-time analytics integration are potential answers to these problems [18].

Nagarajan and Ponkumar (2025) developed a DL framework to enhance the drug discovery process based on prediction of drug–target interactions, de novo drug design, multi-omics integration, and drug repurposing. The identification of novel compounds and therapeutic applications is achieved using some of the most advanced architectures such as CNNs, transformers and generative models. CNN-attention model is able to get 93% DTI prediction ACC, with AUROC: 96%. The hybrid VAE-GAN model showed a synthesizability rate of 80.8% for molecules, and multi-omics integration yielded very promising results with an ACC rate of 92.6%, a sensitivity rate of 93.4% and a specificity rate of 91.8% in biomarker discovery. The 9.1% utilization rate of drug repurposing for new therapeutic applications was the highest. Overall, the framework shows the potential of DL to boost drug discoveries, lower costs, and support compound invention, patient profiling, and therapeutic development [19].

G. A et al. (2024) suggests an AI- and blockchain-based system for the advancement of pharmacovigilance by automating the detection and prediction of adverse drug reactions (ADRs). ML algorithms such as SVM, K-means, and LSTM are capable of performing classification, predictive analytics, and prioritization of ADR reports, and blockchain allows for the secure and tamper-proof management of data. The integrated approach enhances the drug safety monitoring and timely intervention, with prediction ACC of 85%, 90% and 94% for SVM, K-means and LSTM respectively [20].

Kumar, (2024) analyzed the data using method like descriptive statistics and data visualization followed by testing various ML model such as Light GBM model, RF Classifier, and LSTM Model and found the ACC ranging from 90% to 95.7%. used the dataset from the UCI ML repository with over 161297 reviews and 7 features. Since the reviews didn't have sentiment labels came up with the new method, assigned

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sentiment labels on the ratings given by the user either positive or negative. This helped us uncover the hidden sentiment in the reviews. Overall, this research study highlights how people feel about drugs and its impact on experience and treatment outcomes[21].

Lam et al., (2023) aimed to predict the usage demands for commonly used drugs by formulating a regression problem. initial results showed great promise, with the highest RMSE of 0.95 and both R-squared and Adjusted R-squared values of 0.81 belonging to RF. Through continuous endeavors, aspire to enhance the ACC and effectiveness of drug demand forecasting in the pharmaceutical sector and then optimize inventory management, improve resource allocation, and enhance service delivery to meet the healthcare needs of the people of Nghe An province and Vietnam as a whole[22].

Gawich and Alfonse, (2022) The suggested model was tested on the Drugs.com dataset and confirmed using the separate DrugsLib.com dataset. Achieving 87% ACC on Drugs.com and 78% ACC on DrugsLib.com, respectively, were its results. Through sentiment analysis, the model identified adverse drug reactions (ADRs) by grading side effects in patient reviews. Among 213,865 reviews, 44,534 indicated moderate side effects and 66 indicated severe side effects, resulting in an overall ADR detection rate of 21.03% of drug reviews[23].

The table I shows a summary of the recent studies related to Pharmaceutical Drug and Vitamin Image Analysis, including proposed models, datasets used, important results of studies, and barriers encountered

TABLE I. RECENT STUDIES ON PHARMACEUTICAL DRUG AND VITAMIN IMAGE ANALYSIS USING MACHINE LEARNING TECHNQIUES

Author	Proposed Work	Dataset	Results	Limitations & Future Work
G. Sunil et al. (2026)	ResNet50-based drug and vitamin image classification using transfer learning	Kaggle synthetic image dataset	Achieved 98% accuracy, outperforming benchmark models	Limited real-world validation; future work should use larger real-world datasets
Basheeruddin et al. (2025)	Assessed AI (NLP, ML, DL) in drug discovery phases; meta-analysis of drug-target interaction prediction	Drug–Target Interaction (DTI) datasets	Pooled accuracy: 0.57 (95% CI: 0.38–0.76) using DerSimonian–Laird random effects model	Data heterogeneity, interpretability issues, ethical governance; future: XAI, multi-omics fusion, real-time analytics
Nagarajan and Ponkumar (2025)	Deep learning framework (CNNs, transformers, generative models) for DTI, drug design, repurposing	Multi-omics and molecular datasets	DTI accuracy: 93%, AUROC: 96%; VAE-GAN synthesizability: 80.8%	Computational complexity; future: improved scalability, clinical validation
G. A et al. (2024)	ML (SVM, K-means, LSTM) + blockchain for pharmacovigilance and ADR detection	Pharmacovigilance/ADR reporting data	Accuracy: SVM 85%, K-means 90%, LSTM 94%	Data integration challenges; future: scalable blockchain-ML integration
Kumar (2024)	ML sentiment analysis using LightGBM, RF, LSTM on drug reviews	Drug Review Dataset	Accuracy: 90%–95.7%	Lack of labeled data; future: better labeling strategies and real-world deployment
Lam et al. (2023)	Drug demand forecasting using regression (Random Forest)	Pharmaceutical demand data (Vietnam, Nghe An province)	RMSE: 0.95; R^2: 0.81	Regional limitation; future: broader geographic validation
Gawich and Alfonse (2022)	Sentiment-based ADR detection using ML on drug reviews	Drugs.com + DrugsLib dataset	Accuracy: 87% (Drugs.com), 78% (DrugsLib); 21.03% ADR indication rate	Dataset bias and generalization issues; future: robust cross-dataset validation

Research gaps: Previous research has been carried out mainly in the fields of drug discovery, pharmacovigilance, adverse drug reaction detection, sentiment analysis, and pharmaceutical demand forecasting, based on textual, molecular and clinical data. However, few studies have been performed on automatic identification of pharmaceutical drugs and vitamins from a set of pill images. Moreover, most image-based studies focus on DL models, and ensemble ML techniques for pharmaceutical image classification are not widely explored. Thus, the requirement for an efficient and reliable ML model to classify pharmaceutical drugs and vitamin products with their visual features is required.

III. RESEARCH METHODOLOGY

The proposed methodology employs the NLM Pill Image Dataset for pharmaceutical drug and vitamin image classification. Duplicate photos were deleted, images were shrunk, data wasaugmented, labels were encoded, and the dataset was standardized using Min-Max normalization. The dataset was then divided into training, validation, and testing sets. ACC, PRE, REC, F1, confusion matrix, and ROC curve measures were utilized to assess the performance of the RF model that was employed for classification. This is the proposed Flowchart for the Pharmaceutical Drug and Vitamin Image Analysis shown in Fig.1.

The following section presents a detailed description of each stage involved in the proposed methodology:

A. Data Gathering and Analysis

This study utilizes the Pill Image Dataset obtained from the NLM. The dataset contains approximately 7,000 pill images representing 1,000 unique pills, categorized as reference and consumer images. Data visualization techniques, as presented below:

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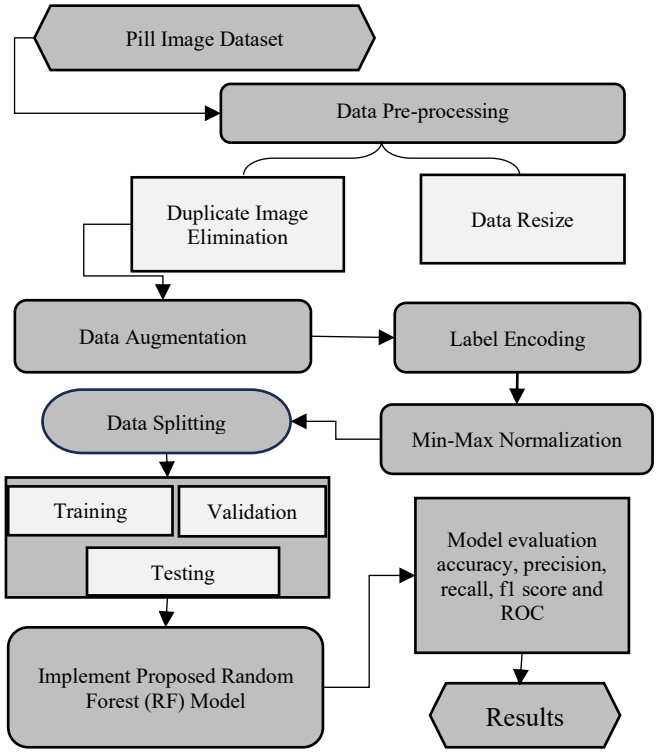

Fig. 1. Proposed flowchart for Pharmaceutical Drug and Vitamin Image Analysis using machine learning

Fig. 2. Images of type of pills

Fig. 2 depicts a series of pharmaceutical pills and capsules of various shapes, sizes, colors and imprinted characteristic. The image depicts a variety of oral medications, including tablets, hard gelatin capsules, and soft gelatin capsules, all of which are commonly used in healthcare [24]. These visual features and manufacturers' markings are very important for identification and classification of pharmaceutical drug and vitamin products [25].

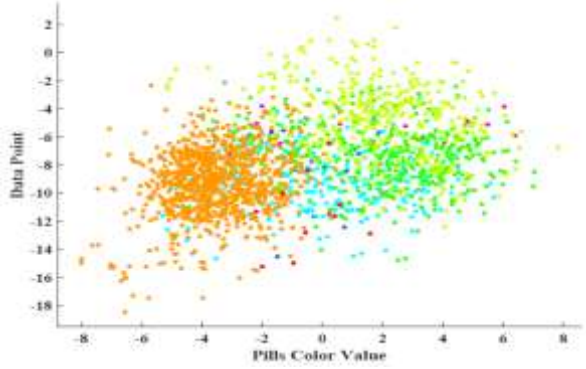

Fig. 3. Scatter plot showing the data points of each pills

The pill data points are plotted in a scatter plot in Fig. 3, based on the values of the extracted features. The plot shows several distinct and overlapping clusters, indicating differences in pill characteristics, such as color and appearance. The spatial distribution of the data areas also reveals the variety of classes of pills in the data, as well as the usefulness of feature representation for classification applications.

B. Data Pre-processing

The Pill Image Dataset was utilized for data preparation, which involved data cleaning and preprocessing to enhance dataset quality and model performance. The pre-processing phases were Duplicate Image Elimination, Image Resizing, Data Augmentation, Data Labeling, and Normalization. The primary steps in the preprocessing are briefly described:

- **Duplicate Image Elimination:** Any duplicate images were detected and excluded from the data set to avoid bias in learning and redundancy. This process enhanced the quality of the datasets and guaranteed that each sample added a unique contribution to model training.
- **Data Resize:** To eliminate duplicate data, use the Remove Duplicates feature in spreadsheet software such as Excel or Google Sheets by selecting the range of data, navigating to the Data tab and clicking Remove Duplicates to indicate the columns to be checked.
- **Data Augmentation:** Explore approaches such as data augmentation which involve random rotations, flips, or color jittering to artificially expand the dataset size and enhance the generalizability of the model.
- **Label Encoding:** Assign a label to each image that identifies the pill by its name and any other characteristic (such as color, shape, imprint, etc.). Manual or crowd sourcing can be used for this labelling.

C. Min-Max Normalization

The Min–Max scaling technique was employed to normalize the values of the features between 0 and 1. This process led to better classification results, faster model convergence and decreased sensitivity to the scale of the features. The normalization procedure was mathematically represented in Equation (1):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X represents the original value of the feature, X' is the normalized value, X_{min} is the minimum value of the feature, and X_{max} is the maximum value of the same.

D. Data Splitting

The data was split into three sets – training (60%), validation (20%) and testing (20%) – distributed evenly between anterior and posterior tablet images across all sets to reduce potential bias.

E. Proposed Random Forest (RF) Model

RF model is applied to classify and identify drug and vitamin products with high ACC according to the extracted image features, so that image recognition of pharmaceutical products can be conducted reliably and automatically in the field of Pharmaceutical Drug and Vitamin Image Analysis. RF

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is a supervised ensemble learning algorithm that uses the combination of multiple decision trees to boost classification ACC and minimize overfitting. The model builds many decision trees during the training process and merges the results to make a prediction. The combination of bootstrap sampling and random feature selection make it robust and generalizable, making it appropriate for many complex classification problems. Each individual decision tree can be used to make a single prediction, which is represented as Equation (1):

$$h_t(x) = c \tag{1}$$

where $h_t(x)$ is the prediction of the t^{th} decision tree and ccc is the predicted class label.

RF constructs several decision trees from different subsamples of the training set. Data patterns are learned independently by each tree, and the diversity of trees decreases the variance of predictions and increases classification ACC. All trees vote a majority to arrive at the final prediction. Finally, this final Random Forest prediction is achieved by Equation (2).

$$H(x) = mode\{h_1(x), h_2(x), \dots\dots, h_T(x)\} \tag{2}$$

where $H(x)$ is the final predicted class, $h_i(x)$ is the prediction of the i^{th} decision tree and T is the number of trees in the forest.

The RF algorithm is also well suited for drug classification and healthcare applications due to its ability to process high dimensional data, nonlinear relationships, noisy datasets while maintaining high predictive ACC. The ensemble structure enhances the reliability and generalization ability, which makes it an excellent choice for pharmaceutical data analysis and classification tasks.

The proposed RF model was set with 100 decision trees (n_estimators = 100) and a maximum tree depth of 20 (max_depth = 20) to ensure a balance between classification ACC and computational costs. The model used gini impurity (criterion = "gini") to split nodes and 2 as the minimum samples split (min_samples_split) and 1 as the minimum samples leaf (min_samples_leaf). Also, max_features = 'sqrt' and random_state = 42 were used to enhance the feature diversity and ensure reproducible results.

F. Evaluation Metrics

The proposed model was evaluated by some of the standard classification metrics. A confusion matrix was first created to visualize the classification results and present the classification results by comparing the classification class labels with the true class labels. The basic measures of TP, FP, TN and FN were provided in the confusion matrix. To assess the effectiveness and reliability of the classification system proposed, values such as ACC, PRE, REC, and F1 score were calculated from these values. These mathematical representations are given below:

Accuracy: ACC is the rate of correctly classified instances to total number of instances in the dataset. It indicates the overall prediction ability of the trained model, and is represented by Equation (3)-

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \tag{3}$$

Precision: Precision is the percentage of positive instances correctly predicted by the model. It allows to assess the ACC of the classifier when it comes to detecting the positive samples, but also to decrease the number of false positive predictions. The PRE metric is shown as Equation (4)

$$Precision = \frac{TP}{\text{TP+FP}} \tag{4}$$

Recall: REC is the ratio of correctly predicted positive instances to the number of actual positive instances that exist in the dataset. It is the performance of the model identifying all the relevant positive cases, mathematically expressed in Equation (5)

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

F1 score: The F1 score is a balanced measure of the PRE and REC that a classifier achieves. It is a number between 0 and 1 and is written in Equation (6).

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

Receiver Operating Characteristic Curve (ROC): ROC curve is a plot of the TPR vs FPR at different decision levels or classification thresholds. In this case, TPR is also referred to as sensitivity or REC, and FPR is equal to 1-specificity. The ROC curve is used for assessing the model discriminatory power.

IV. Results And Discussion

This section outlines the experimental setup and compares the performance of the proposed model in terms of its effectiveness, ACC, and computational efficiency on the experiments performed.

A. Experimental Setup

The system and baseline were used with PyTorch and were trained on a single machine with OS, win 11; CPU, 12th Gen Intel(R) Core (TM) i7-12650H@2.30 GHz, 32 GB of RAM. The experimental platform was developed using the Python programming language and PyTorch framework.

B. Performance Results

The proposed RF model was trained and the performance of the proposed RF model was assessed on the Pill Image Dataset by means of standard classification metrics such as ACC, PRE, REC and F1, as shown in Table II. The results of the experiments indicate that the model is reliable for Pharmaceutical Drug and Vitamin Image Analysis with ACC of 98.5%, PRE of 99.9%, REC of 98.5%, and F1 score of 98.9%. The results indicate that the proposed RF model is robust and provides good classification performance with good PRE and REC, proving that it is robust and capable of automated pharmaceutical image recognition for applications such as computer-assisted systems.

TABLE II. Classifiction results of proposed model Pharmaceutical Drug and Vitamin Image Analysis

Matrix	Random Forest (RF) Model
Accuracy	98.5
Precision	99.9
Recall	98.5
F1-score	98.9

Fig. 4 shows the confusion matrix of the proposed RF model for the Pharmaceutical Drug and Vitamin Image Analysis. As can be seen in the matrix, the majority of samples

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are correctly classified because the values are close to the main diagonal and the values along the diagonal are near zero. This illustrates the model's capability to correctly classify the various drug and vitamin categories with very few misclassifications. The small classification error rate indicates the ability of the RF model to learn discriminative image features with high classification ACC, PRE, and REC rates, and provides good performance on the Pill Image Dataset.

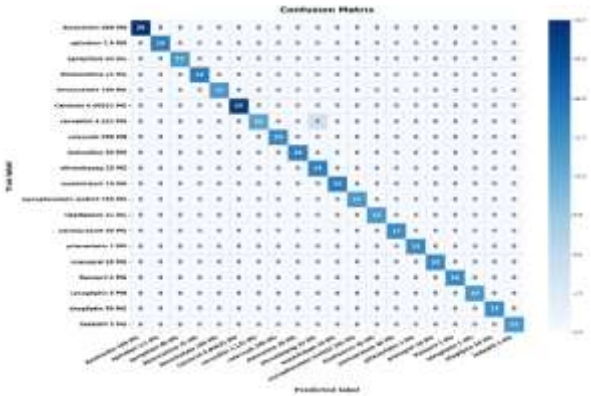

Fig. 4. Confusion Matrix for the Proposed RF Model

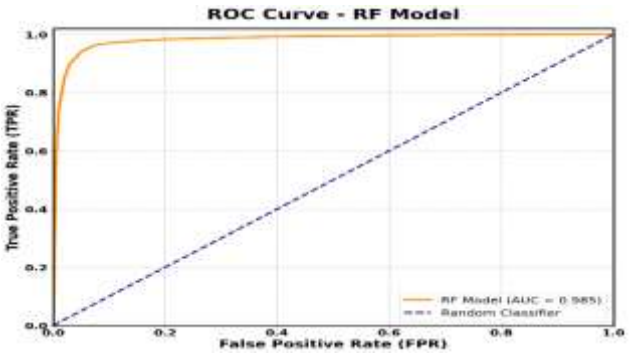

Fig. 5. ROC Curve for proposed RF Model

The suggested RF model for Pharmaceutical Drug and Vitamin Image Analysis is shown in Fig. 5, which is the Receiver Operating Characteristic (ROC) curve. With a TPR around 1 and a False Positive Rate (FPR) close to 0, the ROC curve is located in the upper left corner of the graph, indicating excellent classification. The model's AUC was 0.985, showing strong discriminative strength across several vitamin and medication categories. When compared to the random classifier (diagonal line), the suggested RF model's class power is significantly higher, demonstrating its competence and dependability for pharmaceutical picture classification tasks.

1) Comparative Analysis

The efficacy of the proposed technique is evaluated by comparing its performance with existing DL and ML models, which are provided in Table III. The results of the classification tests for Pharmaceutical Drug Image Analysis and Vitamin Image Analysis show that the suggested RF model fares better. In particular, ResNet-50 achieved 71.7% ACC, CNN and YOLOv5s achieved 93.7% and 97.8% respectively. The proposed RF model achieved an ACC of 98.5%, PRE of 99.9%, REC of 98.5%, and F1 of 98.5% which is better than all of the competing methods. The results showed that the model has been improved in predicting, robustness and reliability and is useful for accurate pharmaceutical drug and vitamin image classification.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING AND DEEP LEARNING MODELS FOR PHARMACEUTICAL DRUG AND VITAMIN IMAGE ANALYSIS

Model	Accuracy	Precision	Recall	F1-score
ResNet-50[26]	71.7	-	-	-
CNN[27]	93.7	92.4	91.3	91.8
YOLOv5s[28]	97.8	95.7	94.3	95
Proposed RF Model	98.5	99.9	98.5	98.5

2) Discussion

The proposed RF model outperformed the existing models like ResNet-50, CNN, YOLOv5s with an ACC of 98.5% in the Pharmaceutical Drug and Vitamin Image Analysis field, achieving better and better results as time goes on. The main advantage of the RF model is that it can handle high dimensional image features, and overcome over fitting through ensemble learning and majority voting. The model also has good PRE (99.9%) and REC (98.5%) values, meaning that it correctly classifies most of the data while making very few mistakes. Furthermore, it is very solid, efficient in computation and possesses good generalization capabilities that make it suitable for automatic image recognition/classification system of pharmaceutical images.

V. CONCLUSION AND FUTURE STUDY

AI and ML technologies have grown in significance for automated pharmaceutical image analysis, enabling precise identification and classification of pharmaceutical products and vitamins and minimizing manual workload and medication-related mistakes. Pharmaceutical image data are increasingly becoming available, which has opened the door for the development of intelligent systems for assisting with healthcare decisions and drug verification. In this work, a ML framework for Pharmaceutical Drug and Vitamin Image Analysis was developed, which is based on the NLM Pill Image Dataset. The suggested method included the data preprocessing, normalization, and classification of pharmaceutical products using the RF algorithm. Experimental results showed excellent classification ACC, PRE, REC and f1 score of 98.5%, 99.9%, 98.5% and 98.9% respectively. Moreover, the ROC analysis generated AUC value of 0.985, signifying good discriminatory power. Comparative analysis showed that the proposed RF model outperformed ResNet-50, CNN, and YOLOv5s models in classification ACC. The results indicate that the proposed automated image recognition framework is effective, robust, reliable, and has the potential to be applied for medication identification, pharmaceutical product verification, and healthcare decision support.

Future studies could focus on integrating more sophisticated D: models, such as Convolutional Neural Networks (CNNs), Efficient Net, and Vision Transformers, to improve the performance of classification. Furthermore, the use of larger and more diverse image datasets, synthetic generation methods, and hybrid ML DL methods can be explored to enhance scalability, generalization and applicability to real-world.

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Ethical Considerations: The dataset used in this study obtained from an open-access source. The dataset contains no identifying, private, or sensitive patient data. The study did not require institutional ethics approval or informed consent because it used secondary anonymized data.

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