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Counterfeit Medicine Recognition System

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Abstract: Counterfeit and misbranded drugs remain a major challenge in contemporary healthcare, threatening patient safety and treatment efficacy. To overcome this critical challenge, a hybrid system is constructed that combines Optical Character Recognition (OCR), Scale-Invariant Feature Transform (SIFT) algorithm, and state-of-the-art preprocessing methods for automated drug identification and authentication. This system processes both text and image data from medicine packs, making it extremely adaptable to different packaging types and real-world image differences. The underlying novelty is the combination of OCR-based data extraction with SIFT-based visual feature analysis, enhancing robustness even with inhomogeneous lighting, orientation, and background conditions. The two-modality solution increases accuracy in medicine verification but at real-time capability. It offers fast and accurate verification, is multilingual text recognition compatible, and fits any format from tablets to injectables and syrups. Performance is assessed using critical parameters such as F1-score, recall, precision, and accuracy over a customized dataset with reliable consistency across various input scenarios. By being a scalable, portable, and efficient solution, the system described here has a high potential for adoption in pharmacies, hospitals, and rural medical centers and has the capability to increase drug traceability and patient safety in day-to-day medical practice.
Keywords: Medicine Identification, Optical Character Recognition (OCR), SIFT, Feature Matching, Counterfeit Detection.

I. INTRODUCTION

Over the last few years, there was a rapid growth of fake and mislabelled drugs, posing a major risk to public health. Mis authentication of drugs can cause dangerous drug interactions, wrong treatments, and, in extreme cases, death. To overcome this issue, new technologies need to be created that can be used at the point of care for real-time authentication and classification. The combination of computer vision and artificial intelligence technology has great potential in solving this problem. The most efficient way is using object detection algorithms like YOLOv4 with Optical Character Recognition (OCR) to enable effective identification and categorization of drugs [1]. The integration allows for more automation in drug verification through both visual identification and label reading. Besides this, OCR-based technologies have been utilized effectively to read vital information like expiration dates and batch numbers on medicine packaging, so that errors resulting from manual entry of data are less likely [2]. Optical character recognition is also crucial for reading handwritten medical prescriptions, a task most typically linked with human error [3]. Prescriptions and paper records are scanned into computer-readable format using the optical character recognition (OCR) technology, which provides greater data accuracy and quicker medical processes [4]. The evidence indicates that the identification and detection of drug information are greatly improved when algorithms of machine learning, especially K-Nearest Neighbours (KNN), are combined with the most recent technology such as Tesseract OCR [5].

II. LITERATURE REVIEW

Recent advances in artificial intelligence (AI) have profoundly impacted medical prescription analysis, where AI techniques are employed to maximize automation, accuracy, and perceptual insight into prescriptions. Many techniques have been proposed, using natural language processing (NLP), computer vision, and machine learning for extracting, analyzing, and categorizing prescription data successfully. A detailed review has scrutinized diverse artificial intelligence methodologies adopted in medical prescription evaluation, emphasizing areas such as prescription validation, drug recommendation systems, and error detection. It highlights the implementation of supervised as well as unsupervised learning methods in managing structured and unstructured medical data, addressing areas such as recognition of handwritten texts and dosage interpretation [6]. The union of regular expressions and supervised learning has shown to effectively improve the precision of classifications in clinical text files. The unifying approach helps in identifying medical entities with precise accuracy and context-aware classifications and has proven extremely useful in semi-structured clinical data sets where traditional natural language processing methods do not work so well [7]. Image processing has become increasingly important in the process of digitizing handwritten and printed prescriptions. The use of Optical Character Recognition (OCR) with Tesseract in a prescription information extraction system demonstrates the stability of machine text extraction of scanned documents.

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The technique employs preprocessing operations like binarization, noise reduction, and morphological processing in order to enhance the accuracy of OCR. The text obtained from the above steps is then formatted into data and is made user-friendly to be used in electronic health records [8]. Scale-invariant feature transform (SIFT) is a core concept in feature-based image analysis. A theoretical algorithmic model describes how SIFT identifies keypoints in images and describes them invariantly to illumination, orientation, and scale. Its application varies from prescription template recognition to object detection in medicine labels and signature verification [9]. Enhancements over traditional SIFT matching with context-aware mechanisms have been shown to demonstrate spectacular improvement in finding matching regions in noisy or cluttered images, leading to enhanced robustness in real-world medical image databases [10].

A method in image forensics has demonstrated the effectiveness of using Scale-Invariant Feature Transform (SIFT) descriptors and the Fast Library for Approximate Nearest Neighbours (FLANN) in verifying image content. The method has demonstrated effectiveness in verifying the integrity of electronic prescriptions and avoiding images from being tampered with, an aspect that is critical in medical forensics and legal adherence [11]. A hybrid content-based image retrieval system combining ORB and SIFT features was proposed to enhance prescription image matching. The combination enhances retrieval speed and precision through the use of ORB's speed and SIFT's stability, rendering it suitable for detecting medical documents under different conditions [12]. SIFT-based feature combination techniques and Oriented FAST and Rotated BRIEF (ORB) have been used in content-based image retrieval systems.

The applications are especially beneficial in drug image searching and prescription template matching. ORB provides real-time processing benefits, and SIFT provides robust feature detection, and therefore their fusion is most appropriate for medical applications where speed as well as accuracy is needed [13]. Improvements to the FLANN algorithm have been proposed to increase the speed and efficiency of image matching when employed in conjunction with SIFT features. This is especially important in large medical databases where there is a need to quickly match prescription templates or labels [14]. Further, learning-based improvements to the RANSAC algorithm have been proposed to improve model selection when dealing with noisy data. These methods facilitate more efficient filtering and matching schemes even in situations where prescription images can be degraded, occluded, or partially visible [15].

Whereas several approaches have been proposed for prescription analysis based on OCR and feature-based image processing methods [6]–[15], many suffer from limitations that hinder real-world applicability. Most existing systems predominantly rely on either text-based processing via OCR or visual similarity techniques such as SIFT/ORB, rather than integrating both modalities within a cohesive framework.

This single-modality dependency significantly reduces performance when handling real-world prescriptions, which often feature complex layouts, handwritten content, stamps, and images of medication packaging that demand both textual and visual understanding. A second critical gap lies in the handling of low-quality, noisy, or degraded prescription images, which are common in resource-constrained clinical environments. Despite advancements in OCR and FLANN algorithms [10]–[14], current methods remain sensitive to noise, occlusion, and scale variations. Furthermore, the absence of real-time, on-device processing limits scalability, particularly in rural or mobile healthcare settings. In contrast, the proposed work introduces a novel multimodal framework that seamlessly integrates OCR and feature matching within a unified pipeline, enabling simultaneous text extraction and visual confirmation.

Unlike previous approaches, the proposed methodology leverages hybrid image descriptors (combining SIFT and ORB features), along with optimized preprocessing techniques and contextual filtering, to significantly enhance robustness against noisy or low-resolution inputs. Additionally, the system is specifically optimized for execution on low-power edge devices, supporting real-time medicine identification in offline environments—a critical requirement for rural telemedicine applications. The novelty of the proposed work lies in its multimodal integration, real-time lightweight architecture, and strong resilience to real-world variations, effectively addressing several practical challenges that earlier methods have overlooked.

III. METHODOLOGY

PIRCS system, proposed here, makes use of image processing and OCR for identifying medicines through analyzing name, shape, and label text. Images are captured and processed to achieve text using Tesseract OCR and identified later through feature matching techniques for the proper identification of medicines.

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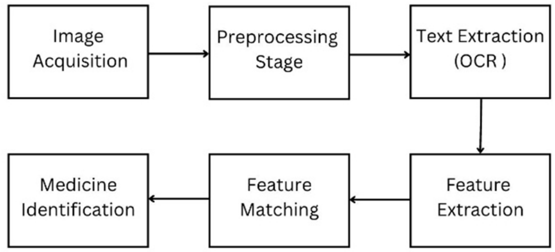

Fig.1 System Architecture for Medicine Identification

As illustrated in Figure 1, the proposed multimodal prescription analysis framework involves a sequence of stages including image acquisition, preprocessing, OCR-based text extraction, feature extraction, feature matching, and final medicine identification.

The dataset contains images of commonly taken drugs taken under different lighting conditions and orientations. Each image is subjected to preprocessing steps like resizing, grayscale, and noise removal to enhance OCR accuracy. Labeled data is employed for feature-based classification

Complementary structured textual data includes detailed information like medicine name, active ingredients, dosage, usage, allergies, and substitutes.

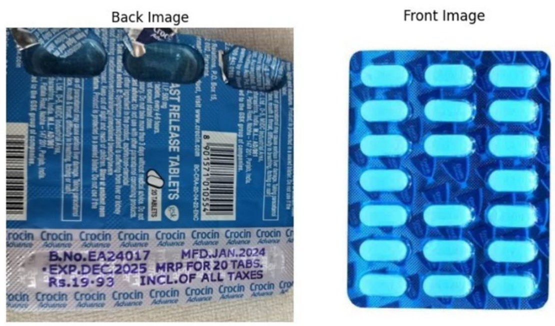

Fig 2. Test Images for PIRCS implementation

Fig. 2 describes the set of test images used for the implementation and evaluation of the PIRCS system. These images represent various medicine samples to assess the identification and classification accuracy.

Table. 1 Image and Text-Based Medicine Information

Data Type	Description
Visual Data	Images of different medicines in different conditions
Textual Data	Medicine name, its active ingredients, dosage, allergies and substitutes

Table 1 presents the types of data utilized in the system, distinguishing between visual data (medicine images) and textual data (medicine-related information such as ingredients, dosage, and substitutes).

- SIFT (Scale-Invariant Feature Transform):

  To find the Gradient magnitude and orientation:

$$m(x,y)=(Lx)2+(Ly)2,\theta(x,y)=\tan-1(LxLy) \qquad (1)$$

where,

Lx : Partial derivative (change) of the image in the x-direction (horizontal).

L : Partial derivative in the y-direction (vertical).

m: Gives the strength of the edge at that point — how sharp or strong the contrast is

θ: Gives the direction of the edge or feature at the pixel

- RANSAC (Random Sample Consensus):

RANSAC fits a model using the largest set of inliers. For example, when fitting a line:

Inlier criterion (error threshold):

$$|y_i - (m x_i + c)| < \epsilon \quad (2)$$

Number of iterations:

$$N = \frac{\log(1-p)}{\log(1-(1-\epsilon)^s} \quad (3)$$

where :

ϵ: expected outlier ratio

s: minimum number of points required

p: desired probability of choosing only inliers

SIFT extracts distinctive keypoints from medicine images that are robust to scale, rotation, and distortion. Equation 1 describes texture around keypoints for matching similar medicine names between images. RANSAC eliminates outliers when matching keypoints in noisy prescription images, using Equation 2 to verify geometric consistency and Equation 3 to determine optimal sampling for reliable matches despite outliers from FLANN or ORB.

Algorithm 1: Medicine Verification using OCR and SIFT

Input: Image of Medicine Packet
Output: Validated Medicine Identity and Extracted Text details
1: Start
2: Capture or upload the image of a medicine packet
3: Apply preprocessing:
  3.1:Convert image to grayscale
  3.2: Apply thresholding
  3.3: Remove noise
4: Perform segmentation to detect Region of Interest (ROI)
5: Apply OCR (Tesseract) on ROI to extract text:
  5.1: Medicine Name
  5.2: MFG Date
  5.3: EXP Date
  5.4: Batch Number
6: Load reference dataset of medicine images and labels
7: For input and reference images:
  7.1: Detect keypoints using SIFT
  7.2: Extract descriptors
8: Use FLANN-based matcher to match descriptors
9: Compute match score between input and reference images
10: if (match score ≥ threshold) then
  10.1: Show extracted text details
  else
  10.3: Display “Medicine Not Verified or Fake”
  end if
11: Store image, extracted data, and verification status in logs
12: End

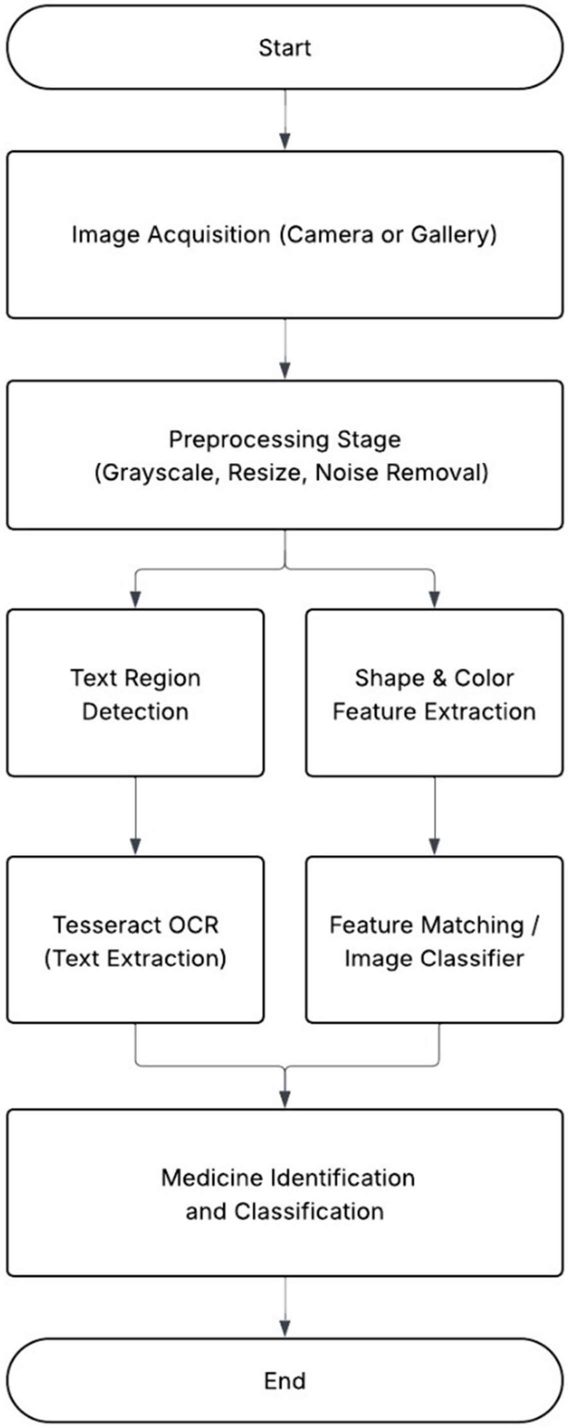

Fig 3. Operational Flow of the Medicine Identification Framework

Figure 3 describes the processing pipeline for medicine identification and classification, which involves image acquisition, preprocessing, parallel text and feature extraction, and final medicine classification based on combined results

The proposed approach combines SIFT-based feature matching, text extraction based on OCR, and image preprocessing in order to effectively identify and authenticate drug packets correctly. Considering the text and picture aspects, it enhances detection as well as delivering reliable categorization and authenticity proof in varied image applications.

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IV. RESULT AND DISCUSSION

The Experimental hardware comprises a high-definition camera to capture images of medicine packets with controlled lighting conditions. The software implementation utilizes Python and OpenCV, Tesseract OCR, and SIFT. The system performs on a testing dataset of medicine images labeled correctly, maintaining steady verification of textual information and image features for widely varying packaging arrangements.

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✅ --- Extracted Fields ---
Medicine_name: Crocin
Mfg_date: JAN.2024
Expiry_date: DEC.2025
Batch_number: EA24017

📝 Data logged to medicine_logs.csv
```

Fig. 4. Extracted Medicine Information for Crocin using OCR and REGEX

Fig. 4 shows the extracted and structured medicine information output generated by the PIRCS system. The displayed details include the medicine name, manufacturing and expiry dates, batch number, active ingredients, strength, dosage form, route of administration, therapeutic class, storage instructions, uses, and important allergy and warning notes.

```
Medicine Name: Crocin

Active Ingredient: Paracetamol (Acetaminophen)

Strength: 500 mg

Dosage Form: Tablet

Route of Administration: Oral

Therapeutic Class: Analgesic/Antipyretic

Storage Instructions: Store below 30Â°C in a dry place.

Uses: Relieves fever, headaches, and mild to moderate pain.

Allergies & Warnings: Avoid excessive use. May cause liver damage in high doses or with alcohol.
```

Fig 5. Additional information fetched from CSV

The medicine name serves as the primary identifier to retrieve detailed information about a drug as given in fig. 5. Once the medicine name is extracted through OCR from an image, it is used to query a CSV file containing a structured dataset of medicine metadata.

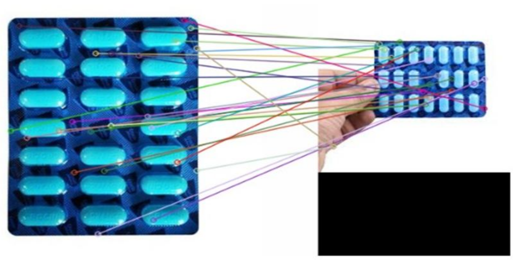

Fig 6. SIFT keypoint detection with FLANN feature matching

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Fig. 6 depicts the feature matching results between a captured medicine image and its reference template in the PIRCS system. The lines represent successfully matched keypoints, validating the system's ability to correctly recognize medicines even under variations like scaling and hand-held positioning.

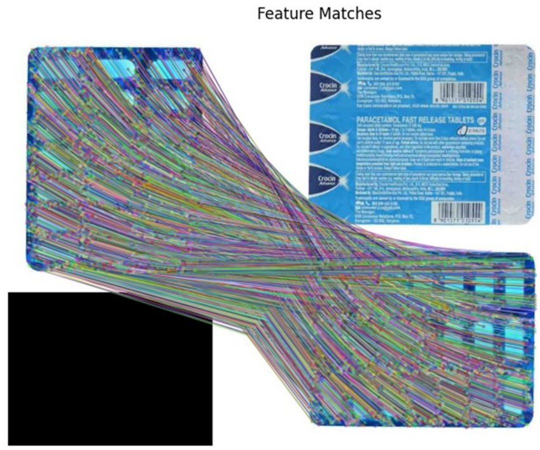

Fig 7. Image result for FLANN + RANSACC

Fig. 7 illustrates the feature matching process between the query image and the reference medicine image in the PIRCS system. The colored lines represent the matched keypoints identified using feature detection algorithms, demonstrating the accuracy and robustness of the matching technique.

Table. 2 Component-wise Performance Analysis of the PIRCS Pipeline

Components	Technique Used	Metric	value
Text Extraction	Tesseract+ OCR+ regex+ Otsu	OCR accuracy (%)	70
Feature extraction	SIFT	Accuracy (%)	82
Feature extraction	ORB	Accuracy (%)	70
Feature Matching	FLANN+ RANSAC	Match Accuracy(%)	93

Table 2. summarizes the techniques used for different components of the system along with their corresponding performance metrics and achieved accuracies.

Statistical analysis of the PIRCS system shows that FLANN and RANSAC have the best match accuracy of 93%, showing good matching of features. Out of feature extraction techniques, SIFT is superior to ORB with a 82% accuracy compared to ORB's 79%. However, the OCR module that is Tesseract and Regex based and Otsu's thresholding has an accuracy of 70%, showing where improvement is needed for text extraction. Overall, the system demonstrates excellent image feature matching performance and average performance in text recognition

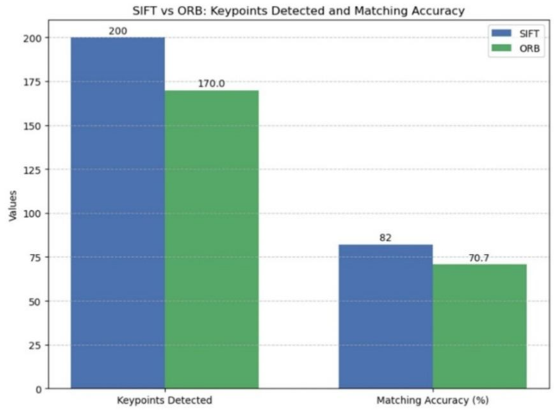

Fig 8. SIFT vs ORB Keypoint detection

Fig.8 compares SIFT and ORB based on the number of keypoints detected and their corresponding matching accuracy, highlighting the superior performance of SIFT in both aspects

The results indicate high stability and precision by using combined OCR and SIFT to achieve both textual and visual characteristics of medicine packets accurately. High F1-Score and AUC values are indicative of the reliability of the model under different circumstances. Misclassification was at times caused by inadequate light, smudged text, or similar packaging. The drawbacks also include dependence on high-resolution images and low precision for handwritten prescriptions. Future improvements may involve training the model with a larger and more diverse dataset, adding object detection through deep learning, and deploying the system on mobile devices for real-time verification and broader application.

V. CONCLUSION AND FUTURE SCOPE

Recent research establishes the growing risk of counterfeiting and misbranding drugs, which completely detracts from patient safety as well as from the efficacy of drugs. Using OCR to extract image-based text and SIFT for visual keypoint matching, we developed an intelligent system capable of successfully identifying drugs using image processing techniques.

The innovation of the solution is its hybridity—textual and image recognition merged together for better robustness, ability to detect manipulated packaging by keypoint matching, and its modularity for easy implementation in healthcare systems or mobile applications. All these make it stronger, more flexible, and scalable verification. The advantages of the system are fast detection, support for multiformat packaging, and high accuracy in low image quality.

Its main limitation lies in its dependency on high-quality images and limited support for printed text on parcels. Future enhancements may include the integration of deep learning models and improved mobile compatibility to facilitate real-time verification and enhance accessibility.

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