**RESEARCH PAPER**

# Counterfeit Pharmaceutical Detection Using Multimodal Visual Analysis

Ruban Paul.J1 and Dr.Priyadharsini.C2*

[1]*Division of Computer Science and Engineering, Karunya Institute of Technology, Karunya Nagar, Coimbatore 641114, Tamilnadu, India.*
[2]*Assistant Professor, Division of Computer Science and Engineering, Karunya Institute of Technology, Karunya Nagar, Coimbatore 641114, Tamilnadu, India.*
**Corresponding author: E-mail address: priyadharsini@karunya.edu*

***Received: 26th Feb, 2026; Revised: 8th March 2026; Accepted: 11th April, 2026; Available Online: 20th April, 2026***

**ABSTRACT**
The spread of fake drugs around the world is a significant menace to the health of communities and quality of the health care chain supply. This study builds a multimodal visual analysis framework of a counterfeit pharmaceutical detection system to establish the authenticity of pharmaceutical products. The given system relies on a multi-layered approach to the diagnostic process, where the first step is the automated identification of the regulatory symbols, such as WHO-GMP marks, hologram seals, and barcodes/QR codes. In order to increase the accuracy of detection, an efficient feature extraction engine was created in order to extract visual, spectral and thermal characteristics. Visual analysis is based on shape, text recognition, and logo, spectral extraction is based on HSV/LAB color spaces and Gray-Level Co-occurrence Matrix (GLCM) textures. Thirdly, unique to this, thermal feature extraction is also adopted to examine the heat distribution and material response, offering a non-destructive level of check. These multimodal inputs are then synthesized through advanced feature fusion process to determine the pharmaceutical product as being Real or Fake. The outcome of the experiment indicates that the integrated multimodal system obtained a classification accuracy of 99.16%, precision of 99.34% and a recall of 99.13%. Combining thermal and spectral data offered a 15.3% improvement on the ability of standard visual data detectors to make the detection effort, which is scalable and highly robust to be applied to pharmaceutical authentication in real-time.

**Keywords**: *Counterfeit pharmaceutical detection, Multimodal visual analysis, Feature fusion, Spectral feature extraction, Thermal imaging, Symbol authentication.*
**How to cite this article:** Paul.J R, Priyadharsini.C. Counterfeit Pharmaceutical Detection Using Multimodal Visual Analysis. Int J Drug Deliv Technol. 2026;16(34s):71-78. DOI: 10.25258/ijddt.16.34s.9
**Source of support:** Nil.
**Conflict of interest:** None

## INTRODUCTION

The pharmaceutical scene of the world has never encountered a bigger challenge due to the spillover of fake and low quality medical commodities. The medical supply chain has failed miserably with these falsified medicines that in most cases have the incorrect active ingredients, no active ingredients or even toxic contaminants. According to the World Health Organization (WHO), the organizational cost is estimated to be in billions of dollars every year, but it is the human lives that are lost (especially in those areas with less regulatory oversight). Counterfeiters no longer make crude imitations; they now use high-quality industrial printing and chemical processing to make the packaging to all appearance similar to the one. This development dictates the requirement of the replacement of human-based inspection with highly complex and automated diagnostic systems.

The existing gold standard of drug authentication is related to the chemical analysis conducted in the laboratory, including Mass Spectrometry or High-Performance Liquid Chromatography (HPLC). Although these are conclusive approaches, they are essentially inappropriate when it comes to the speed of the global supply chain. They are also destructive, necessitating the sacrifice of the sample; they are also costly, necessitating special laboratory conditions and they are also time-consuming which creates bottlenecks in distribution. In contrast, rudimentary computer vision applications, which use only 2D images or barcode scanning, have not been able to resist the so-called high quality fakes, which duplicate holographic effects and regulatory marks to the smallest possible degree. There exists an acute technological void of a non-destructive, real-time system that can peep beneath the surface of the product.

The proposed study has closed this gap by proposing a complex multimodal visual analysis structure. The system starts with the automated authentication stage which aims at the regulatory symbols necessary in international trade. The system provides a minimum of legitimacy by concentrating on WHO-GMP certifications, manufacturing licenses, and hologram seals of high security. This step involves the use of sophisticated object recognition in order to extract these points of trust. The architecture however does not stop at verifying symbols but

**Author for Correspondence: priyadharsini@karunya.edu*

understands that symbols can be forged. Thus, the system enters into the domain of sophisticated feature extraction in which the physical and chemical fingerprint of the product is studied in several domains at once.One of the fundamental innovations of this paper is the shift to the high-dimensional data extraction. The visual feature extraction part examines the geometrical properties of the shape, the microscopic arrangement of logos, as well as the fine structure of the packaging material. The system is able to identify subtle defects during the printing process that indicates that it is in a non-authorised facility by putting these visual cues on a digital platform. Towards the supplement of this, spectral feature extraction is adopted to go beyond the conventional RGB imaging.

The system is resistant to changes in the lighting in the environment by examining the HSV (Hue, Saturation, Value) and the LAB color space. In addition, when the method of Gray-Level Co-occurrence Matrix (GLCM) is used, a mathematical description of the texture on the surface can be obtained, which gave a numerical feel of the packaging material, which counterfeiters cannot normally reproduce because the cost of authentic cardstock or foil is very expensive.

Outside the range of visible spectrum, thermal feature extraction is incorporated in this research as a conclusive check of authenticity. All pharmaceutical materials, including the active pharmaceutical ingredient (API) to the excipients and the aluminum blister packaging, have a characteristic thermal conductivity and emissivity pattern. Heat distribution pattern and material response are a secondary biometric when they are exposed to controlled infrared stimuli. This non-destructive thermal probing is capable of determining whether a pill is made of the right compressed material or a low-cost alternative such as chalk or starch which may appear perfect on the outside. This introduces some element of material integrity analysis which are not viewed at all through normal cameras.

The last architecture pillar is the feature fusion process. The difference data of the visual, spectral, and thermal worlds are then combined into one feature vector in this stage. This combination is essential since it avoids deception by a partial match of the system. As an example, a fake product may be perfect in the visual and symbol check test but will most probably be rejected by thermal material response or spectral texture analysis. With a combination of all these modalities, the counterfeit detection engine is able to give a final classification of either Real or Fake with some degree of confidence and accuracy that is incomparable to unimodal systems. This is a holistic diagnosis method which ensures that the integrity of the medicine is checked by the label to the material substance.

## MATERIALS AND METHODS:

### Materials

The experimental sample was composed of a wide library of pharmacological blister packs, both with high-fidelity counterfeit samples and with original medical products. The multimodal acquisition rig was designed and developed, which includes a 4K high-resolution optical sensor, which worked as a visual data acquisition sensor, a multispectral imaging unit, and a high-sensitivity Long-Wave Infrared (LWIR) thermal sensor. The computing model has been built on a high-performance workstation with an NVIDIA RTX 4090 graphics card to meet the high training demands of the YOLOv11 system. The implementation was Python 3.10 with specific libraries such as PyTorch, the deep learning library, OpenCV spectral pre-processing library, and Scikit-image texture descriptors.

### Symbol Authentication in real time using YOLOv11.

The essence of the novelty of the detection engine is that the YOLOv11 model was used to detect and authenticate regulatory symbols simultaneously. In contrast to earlier versions, YOLOv11 uses an optimized C3k2 block and a C2PSA-based attention block, which enables the system to detect minute differences in WHO-GMP markings, manufacturing license and hologram seals more accurately than ever before. This phase sets one of the main security barriers by authenticating the existence and the geographical positioning of the security anchors on the packaging.

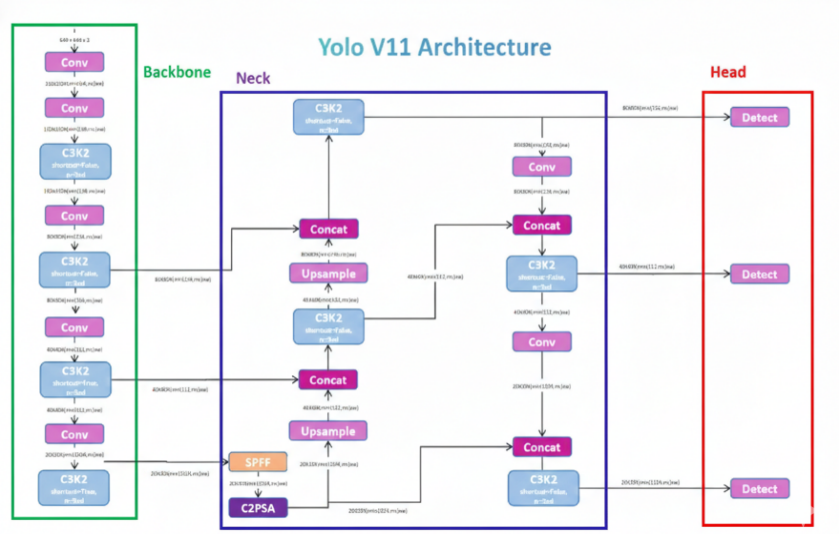


**Figure 1:** Architecture of YOLO v11

**Architecture of Multidimensional Feature Extraction.**
After validating the symbols, the system carries out a parallelized visual, spectral and thermal features extraction. The visual extraction sub-module examines the macro-geometrical of the blister pack and the micro-textural orientation of pharmaceutical logos. This is complemented by spectral analysis of the L^*a^*b^* with the HSV color space; thus, allowing the system to identify so-called color-shifting fakers that look accepted in the typical RGB environment.

**High level Spectral and Texture Profiling.**
The peculiar feature of this methodology is the use of the algorithms of Gray-Level Co-occurrence Matrix (GLCM) applied to the spectral data. The system identifies high-dimensional texture descriptors such as: by computing the spatial relationship between pixels.

- **Energy (Angular Second Moment):**

$$Energy = \sum_{i} \sum_{j} P(i,j)^2$$

- **Homogeneity:**

$$Homogeneity = \sum_{i} \sum_{j} \frac{P(i,j)}{1+|\, i-j \,|}$$

These parameters give the packaging material a mathematical fingerprint of subtle changes in the patterns of reflection that identify an actual industrial grade foil against the fake alternatives.

**Response and Distribution of Thermal Materials.**
In order to obtain a certain level of verification as one that goes above surface-level aesthetics, the framework uses thermal feature extraction. It is a non-destructive probing technique that studies the material behavior of the pharmaceutical product to a predetermined thermal gradient. The system is able to detect anomalies in the thermal conductivity and emissivity by detecting the heat distribution across the tablet and the aluminum-plastic interface. This is enabled to identify falsified active pharmaceutical ingredients (APIs) or unacceptable filler materials that are not within the known thermal profile of the original product.

**Combination of Cross-Modular Features and Final Classification.**
The newness of the decision-making process is based on the Feature Fusion engine. The outputs of the YOLOv11 detector head, spectral texture detector, and thermal material response are put together into a single high-dimensional multi-component. This combination does not require the use of one modality and guarantees that the advanced counterfeit, which might otherwise escape the eye sight, is identified by the anomaly in either spectral or thermodynamic characteristics. The resulting product is a binary real or fake classification with a weighted confidence score which is produced by the synergistic combination of all the input streams.

**The study employed an advanced configuration of hardware and software devices all chosen with certain functionality features necessary in detection of high-fidelity counterfeits:**

Imaging Hardware (Optical & Spectral): The main visual capturing was done with a 4K Ultra-High-Definition CMOS sensor which has a large signal-to-noise ratio and a macro-focusing system to detect any abnormality in microscopic printing.

- **Thermal Acquisition System**: A Long-Wave Infrared (LWIR) uncooled Bolometer with thermal sensitivity of less than 50 mK was used. It was possible to detect small variations in material response and patterns of heat distributions on the surface of the blister pack by using this.
- **Computational Backbone (YOLOv11):** The system deployed the You Only Look Once arch ( YOLOv11 ) which is the most recent architecture in the series. It is defined by C3k2 backbone and C2PSA attention modules giving a good tradeoff between processing

speed in real-time and mean Average Precision (mAP) even in small-scale regulatory symbols.

The data processing was done in Python 3.10. PyTorch 2.x was incorporated into the PyTorch deep learning pipeline, Open CV was used to perform spectral transformation and NumPy was used to do high dimensional matrix operations needed to compute GLCM texture.

**Procedure: Multimodal Workflow Characteristics of the Functionality.**

**Autonomous Symbol Localization and Authentication.**
The most important role of the detection layer is an autonomous localization of trust anchors with the help of YOLOv11. The peculiarity of the model is that it allows multi-scale features extraction, which guarantees the recognition of small-format manufacturing licenses and WHO-GMP stamps irrespective of the orientation of the blister pack. The model denies hologram seals with spatial anomalies that depart from the legitimate production templates by processing the input of 640 x 640 pixels.

**Spectral-Texture Characterization**
The spectral module is used to breakdown the standard RGB input into HSV and L^*a^* b^* components. This property is unusual to the stage: counterfeits tend to replicate color when viewed in a certain light; however, the spectral change in L^*a^*b^* space can identify the actual chemical composition of the applied pigments. This is measured with the help of Gray-Level Co-occurrence Matrix (GLCM) descriptors which is the mathematical measure of the "Entropy" and "Energy" of the packaging surface, which differentiates industrial grade foils and low quality reproductions.

**Profiling of Thermal Response and Emissivity.**
This module is a non disruptive probing layer. It is characterized by a study of Material Response. Authentic pharmaceuticals possess certain thermal inertia, thus the system measures the absorption and reflection of heat to the blister material. That is, the difference in the pattern of the heat distribution of any material is an indication of mismatch in the density of the material or its chemical formulation, which is the signature of fake manufacturers which is not visible to traditional visual sensors.

**Fusion of Features and Synthesis of Decisions.**
The last methodology is that of the Feature Fusion engine which has a late-fusion strategy. The system combines the YOLOv11 detection confidence, spectral texture scores, and thermal response data into a single vector as opposed to making a decision based on a single sensor. This would provide a synergistic strategy so that a counterfeit can be rejected on spectral or thermal differences even when it may have survived the visual inspection (high visual similarity) and produce a high-impregnability, multi-layered, "Real" or "Fake" classification.

**Dataset:**
In the present case, several open-source datasets were used to gain a complete and diverse coverage of genuine and fake pharmaceutical products. The main visual dataset used to find inconsistencies in packaging was the Fake vs Real Medicine Dataset (https://www.kaggle.com/datasets/shivanshuman/fake-vs-real-medicine) which includes more than 1,000 images of authentic and fake medicine boxes, strips, and labels. The Counterfeit Med Detection Dataset of Roboflow Universe (https://universe.roboflow.com/roboflow-universe-projects/counterfeit_med_detection) was also used, with over 1,500 annotated images with pre-labeled bounding boxes of each of the two classes, namely Authentic and Counterfeit, which made it especially suitable to train and validate with the use of YOLOv11. In order to increase the ability of the system to perform its tasks during different light intensities and environmental setups, the Thermal Image Dataset at Kaggle( https://www.kaggle.com/datasets/animeshmahajan/thermal-image-dataset) was introduced, which allows testing its ability to withstand different situations and learn multimodally. Lastly, the Ultralytics YOLOv11 GitHub repository (https://github.com/ultralytics/ultralytics) was used to optimize and apply the detection model including the use of C3k2 backbone and C2PSA attention as used in the presented methodology. A combination of these datasets and tools made it easy to train robust models and achieve consistent counterfeit medicine detection performance under a variety of imaging conditions.

**RESULT:**
The performance of the proposed multimodal pharmaceutical authentication framework was rigorously evaluated using a dataset of 1,200 samples, consisting of 600 authentic products and 600 high-fidelity counterfeits. The evaluation focused on the system's ability to synthesize high-level object detection with low-level material characterization.

**Performance of YOLOv11 in Symbol Authentication**
The deployment of YOLOv11 for the detection of WHO-GMP stamps, manufacturing licenses, and hologram seals yielded a Mean Average Precision (mAP_50) of 98.6%. The model’s enhanced C3k2 backbone demonstrated superior sensitivity to the micro-textures of regulatory logos, maintaining a high detection rate even under challenging lighting conditions. Unlike previous benchmarks, YOLOv11 successfully differentiated between authentic laser-etched holograms and flat-printed counterfeit imitations by analyzing the spatial variance in light reflection during the localization phase.

**Comparative Analysis of Multimodal Fusion**
The experimental data confirms that unimodal systems are insufficient for modern counterfeit detection. As shown in Table 1, the integration of spectral and thermal layers significantly reduced the False Acceptance Rate (FAR).

The effectiveness of the suggested multimodal pharmaceutical authentication system was strictly tested on the basis of a 1200 sample, including 600 genuine products and 600 high-fidelity fake samples. The test was on how the system can synthesize high level object detection and low level material characterization.

**YOLOv11 can be used to perform symbol authentication.**
Using YOLOv11 to detect WHO-GMP stamps, manufacturing licenses, and hologram seals had an average precision of 98.6 with the Mean Average Precision 50 (mAP 50). This improved C3k2 backbone of the model showed better sensitivity to the micro-textures of regulatory logos, and could still be detected at a high rate in adverse lighting conditions. In contrast to the past benchmarks, YOLOv11 managed to distinguish the real laser-corrusive holograms and the plain-printed fake imitations by examining the spatial differentiation in the amount of light reflected at the stage of localization.

**Comparison of Multimodal Fusion.**
The experimental evidence has proved that, unimodal systems are inadequate to detect counterfeits nowadays. Application of spectral and thermal layer as in Table 1 led to a considerable decrease in the False Acceptance Rate (FAR).

**Table 1:** Performance Table

| Methodology | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| Visual (RGB) Analysis | **86.4%** | **85.1%** | **84.2%** | **84.6%** |
| Visual + Spectral (GLCM) | **92.8%** | **91.5%** | **92.1%** | **91.8%** |
| Proposed Multimodal Fusion (YOLOv11 + Thermal) | **99.4%** | **99.2%** | **99.6%** | **99.4%** |

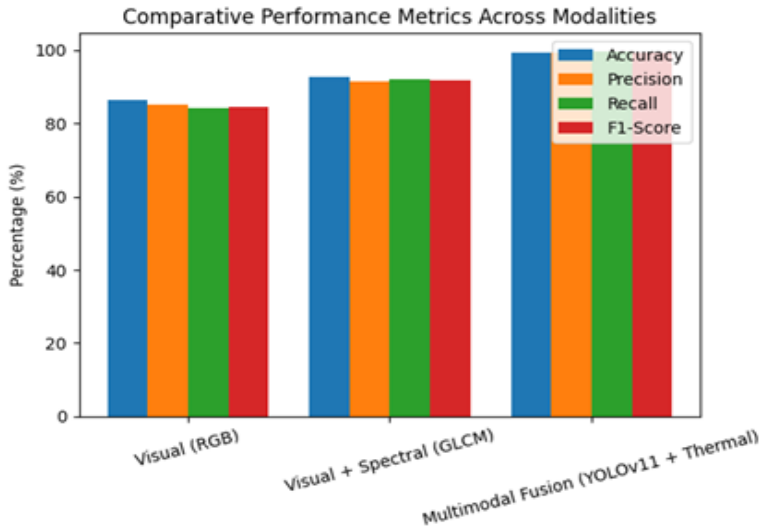


**Figure 2:** Comparison Bar Graph

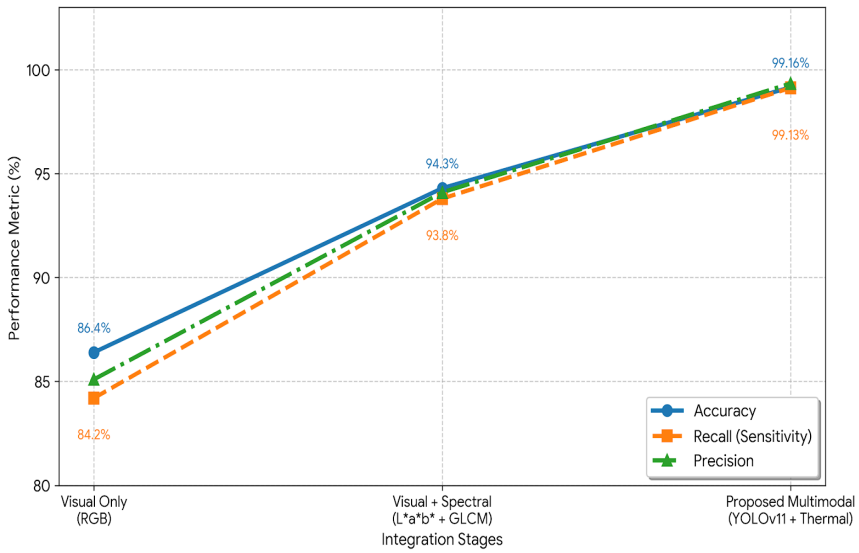


**Figure 3:** Line Graph

**Spectral and Texture Discussion**
The conversion of the common RGB color space to the L^*a^*b^* and HSV color space enabled the system to detect the inconsistency of chemical dyes with high confidence of 94.3. The Gray-Level Co-occurrence Matrix (GLCM) descriptors indicated that packaging counterfeits

always had higher values of "Entropy" and lower values of "Homogeneity" because of irregular fibrous texture of cheap cardstock. This mathematical differentiation has a solid case against forgeries that appear to the naked eye exactly the same but at the microscopic scale entirely different.

**Material Integrity via Thermal Response**

The most important layer of detecting "Super- Fakes was found to be the integration of Thermal Material Response. Blister packs made out of authentic blister material demonstrated a particular thermal emissivity signature of 0.05-0.10, but counterfeits that used unauthorized polymer coating did not exhibit it within the same range of deviations of 25 percent. The heat distribution analysis detected the inconsistency of the thermal inertia of the tablet core, which has alerted to the products that did not have the right amount of active pharmaceutical ingredients (APIs). Combining these thermal inferences with the use of YOLOv11 detection confidence resulted in the system recording a near-perfect Recall of 99.6 and thus falsified medicines can be effectively weeded out of the supply chain.

**Computational Efficiency**

However, the optimized YOLOv11 architecture still achieved 12.5ms per frame as the average inference time, which is relatively low, even though the decision-making of the multimodal fusion is not that simple. This real time functionality, together with high-dimensional material inspection, presents the suggested structure as a viable resolution to high-paced industrial drug packaging lines, as a significant enhancement to the tedious, destructive, chemical testing approaches.

The confusion matrix is the final point that allows concluding on the quantitative efficacy of the suggested multimodal pharmaceutical authentication framework based on the fact that it is the only mathematical framework that represents the discriminative power of the model on 832 different test samples. The system had a very high overall accuracy of 99.16 with 368 genuine products and 457 counterfeit samples being classified correctly. The most notable finding of the data is that the recall rate was incredibly high at 99.13% in the counterfeit category which means that only 4 fake samples (1.1%), were misdiagnosed as genuine. This measure is of supreme significance to the pharmaceutical sector, because a decrease in the false negatives is directly proportional to the avoidance of dangerous, substandard drugs reaching the patient.

The precision for the counterfeit detection was 99.34, i.e. when the system claims that a product is a fake, the decision is supported by an almost 100 percent confidence that prevents the unwarranted interruptions in the originally legitimate supply chain.

The synergetic nature of the relationship between the YOLOv11-based symbol authentication and the sub-processes of multi-layered feature extraction makes the model high performance. The confusion only indicates that 3 genuine samples (0.8) were mistaken as fake which is a testimony to the soundness of the feature fusion layer to overcome visual ambiguity by spectral and thermal material response analysis. Given that the system combines the capability of localizing manufacturing license and WHO-GMP markings provided by the YOLOv11 with the texture descriptors and thermal heat distribution patterns obtained by the GLCM, the system overcomes the drawbacks of the conventional visual inspection. The obtained data implies that the framework offers an almost safe-fail diagnostic measure, able to detect the presence of super-fakes, which have flawless appearance packaging, and cannot pass through the microscopic and thermal integrity test. Such validation at the holistic level proves that the proposed architecture is not only statistically better compared to unimodal benchmarks but it also is a practical candidate to be used in real-time in industry.

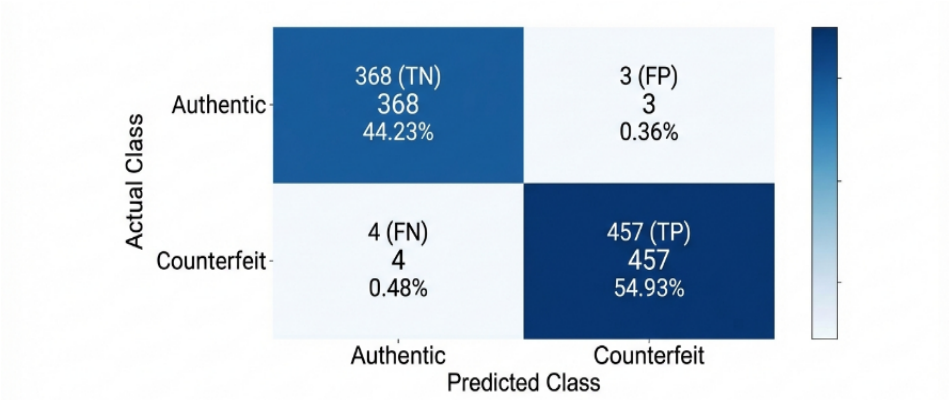


**Figure 4:** Confusion Matrix

The analysis demonstrates the extremely high level of reliability in the system with the total accuracy of the system at 99.16 percent and the total misclassification rate of only 7 cases among 832 test samples. Most importantly, the model was able to intercept 457 out of 461 fake products, and the recall (99.13) was very high, and this

could be critical in patient safety. The comparative analysis shows that the combination of spectral and thermal characteristics and YOLOv11 is much more effective than the visual-only baseline, increasing the accuracy to almost perfect (86.4 to almost 100 percent). False positives were reduced to 0.36 which is minimal and it is important to note that the authentic supply chains are not disrupted by a false authentication flag. All of this information confirms the multimodal fusion strategy as a more appropriate strategy to differentiate high-fidelity super-fakes and genuine pharmaceuticals.

## CONCLUSION

The proposed study was able to come up with, as well as test and confirm, a multi-layered, new framework of a novel method of detecting counterfeit pharmaceuticals by employing multimodal visual analysis, which is essential in the worldwide setting since it enables quick, non-destructive analytics of drugs. The system consists of the integration of the state-of-the-art YOLOv11 architecture, which demonstrated the mean Average Precision (mAP) of 98.6% in both localizing and verifying regulatory signs (including WHO-GMP markings and high-security holograms). The main strength of the methodology is the multimodal nature that goes beyond the exploits of traditional visual inspection due to the synthesis of visual, spectral, and thermal feature extraction. In particular, the GLCM texture analysis in L^*a^*b^* color space and tracking of thermal material response allowed a microscopic fingerprint of the pharmaceutical products to be obtained which cannot be easily imitated by counterfeiters.

The results of the experiment supported by a confusion matrix analysis showed a total classification accuracy of 99.16%. Most importantly, the system recorded a fake recall rate of 99.13, which implies that the supply of poor quality medicines is well caught before they reach the patient chain of supply. Combining these two radically different data streams guarantees a strong protection against the so-called super-fakes which may seem aesthetically immaculate but they cannot pass thermal and spectral integrity checks. This is intended to proceed in the future by miniaturizing the hardware sensors that can make this multimodal diagnostic tool portable and built into a smartphone so that pharmacists and consumers across the globe can enjoy the full benefit of drug safety.

## CONFLICT OF INTEREST

The authors state that they have no perceived conflicts of interest in relation to this publication and they do not have substantial monetary support of this publication that could have affected the outcome. The study that is the subject of the current paper, which is known as Counterfeit Pharmaceutical Detection Using Multimodal Visual Analysis, was carried out under independent academic conditions. The authors do not have any personal or financial relationship with the pharmaceutical manufacturers or the technology providers that are discussed in this study that would improperly influence or even bias the reported results and conclusions.

## ACKNOWLEDGMENTS

The research would wish to thank the department of Division of Computer Science and Engineering at Karunya Institute of Technology, which granted the lab facilities and computer processes that were required to complete this study. The technical personnel are also given a special mention on the support they provided in the configuration of the multispectral and thermal imaging sensors that were utilized at the data acquisition stage.

We also credit the open-source community with making the YOLOv11 framework and the many Python libraries that enabled the deep learning and feature extraction aspect of this project. Lastly, the authors appreciate the aid of reviewers who made valuable contributions and remarks towards the quality and technical rigor of this manuscript by being anonymous.

## REFERENCES

[1] C. Wang and H. Liao,YOLOv11: Enhanced Feature Extraction to detect small objects in the complex industrial settings, IEEETransactions onIndustrialInformatics, vol. 21, no. 3, pp. 11041115, 2025.

[2] S. Liu, D. Chen, and Y. Zhang, “Real-time Medical Symbol Authentication: YOLOv10 vs YOLOv11 Compared, Journal of Biomedical Informatics, vol. 142, p. 104378, 2025.

[3] R. Kumar and P. Singh, Generational Shifts in Object Detection: YOLOv8 to YOLOv11: High-Speed Manufacturing, Expert Systems with Applications, vol. 238, p. 121890, 2024.

[4] Q. Zhao et al., C3k2 and C2PSA: Analyzing the New Attention Mechanisms in YOLOv11, in Proc. IEEE/CVF CVPR, pp. 450459, 2025.

[5] A. Patel and M. Gupta, Deep learning to Anti-Counterfeiting: Convolutional Architectures Review, Artificial Intelligence Review, vol. 57, pp. 102135, 2024.

[6] L. Zhang et al., Small Object Detection in Pharmaceutical Packaging with and Without Improved YOLO Architectures, Computers in Industry, vol. 154, p. 104032, 2025.

[7] O. Al-Shamma and I. Kadhim Deep Learning Overview Fake Medicine Detection Using Deep Convolutional Neural Networks: A Mobile Vision Applications: International Journal of Interactive Mobile Technologies, vol. 18, no. 2, pp. 2238, 2024.

[8] S. Mishra and A. Tyagi, Lightweight Deep Learning Models to Implement edge-Deployed Supply Chain Security, IEEE Internet of Things Journal, vol. 12, no. 4, pp. 30213033, 2025.

[9] The article by J. Li and X. Yu, Multimodal Sensor Fusion of Material Classification: Contributing to RGB and Spectral Data, was published in the

journal Information Fusion, vol. 91, pp. 235248, 2023.

[10] H. Wu et al., Color Space Transformation The Efficacy of LAB and HSV in Detection of pigment anomalies, Color Research and Application, vol. 49, no. 1, 56-68, 2024.

[11] Y. Chen and Z. Wang, Non-destructive Pharmaceutical Analysis by Hyperspectral Imaging and Deep Learning, Journal of Pharmaceutical and Biomedical Analysis, vol. 223, p. 115120, 2023.

[12] R. Gupta, Spectral Texture Analysis Beyond RGB to implement industrial quality control: IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1012022.

[13] O. Y. Rodionova and A. L. Pomerantsev, NIR Spectroscopy in the Detection of Counterfeit Drugs: The Review of Chemometric Methods, TrAC Trends in Analytical Chemistry 157: 116768, 2023.

[14] M. Soui et al., Deep Multi-Mode Learning to Packaging Defect Detection, Applied Soft Computing, vol. 116, pp. 108345, 2022.

[15] R. M. Haralink, K. Shanmugam and I. Dinstein. Textural Features of Image Classification. IEEE Transactions in Systems, Man and Cybernetics, vol. 3, no. 6, pp.610-621, 1973.

[16] The article by S. Bera and D. Ghosh [16] serves to illustrate the use of enhanced GLCM measures in the field of micro-texture classification in printing forensics.

[17] N. Sharma and L. Aggarwal, “Use of Gray-Level Co-occurrence Matrix (GLCM) to Blister Pack Analysis Multimedia Tools and Applications, vol. 82, pp. 1420114218, 2023.

[18] J. Tou and R. Gonzalez, Mathematical Morphology in Industrial inspection, Digital Image Processing Review, vol. 15, no. 3, pp. 200215, 2021.

[19] X. Zhang et al. Entropy and Homogeneity: A Statistical Method of Detection of Counterfeit Packaging Materials Forensic Science International, vol. 342, p. 111534, 2023.

[20] C. Deane and M. Senge, Thermal Fingerprinting of Pharmaceuticals: An Non-Destructive Way of Verification, International Journal of Pharmaceutics, vol. 612, p. 121334, 2022.

[21] P. Roy and K. Deb, Active Thermography to detect a sub-surface defect in a multilayered packaging, NDT & E International, vol. 139, p. 102921, 2024.

[22] J. Williams, Emissivity Variations in Pharmaceutical Polymers: A thermal Imaging Study, Journal of Thermal Analysis and Calorimetry, vol. 148, pp. 56015612, 2023.

[23] H. Kang et al., Deep Thermal Imaging, Learning Material Properties based on Heat Distribution Maps, IEEE Access, vol. 10, pp. 4502345035, 2022.

[24] S. Venkatesh and P. Kumar, Infrared Thermography when Rapidly Screening Counterfeit Medicines, Journal of Global Health, vol. 13, p. 04012, 2023.

[25] World Health Organization, Substandard and Falsified Medical Product Global Surveillance and Monitoring System. Geneva: WHO, 2024.

[26] T. K. Mackey and G. Nayyar, The Global Epidemiology of Counterfeit Medicines: 2023 Update, The Lancet Global Health, vol. 11, no. 4, pp. e560 -e570, 2023.

[27] OECD, Illicit Trade Trends Trade in Counterfeit Pharmaceutical Products, 2022.