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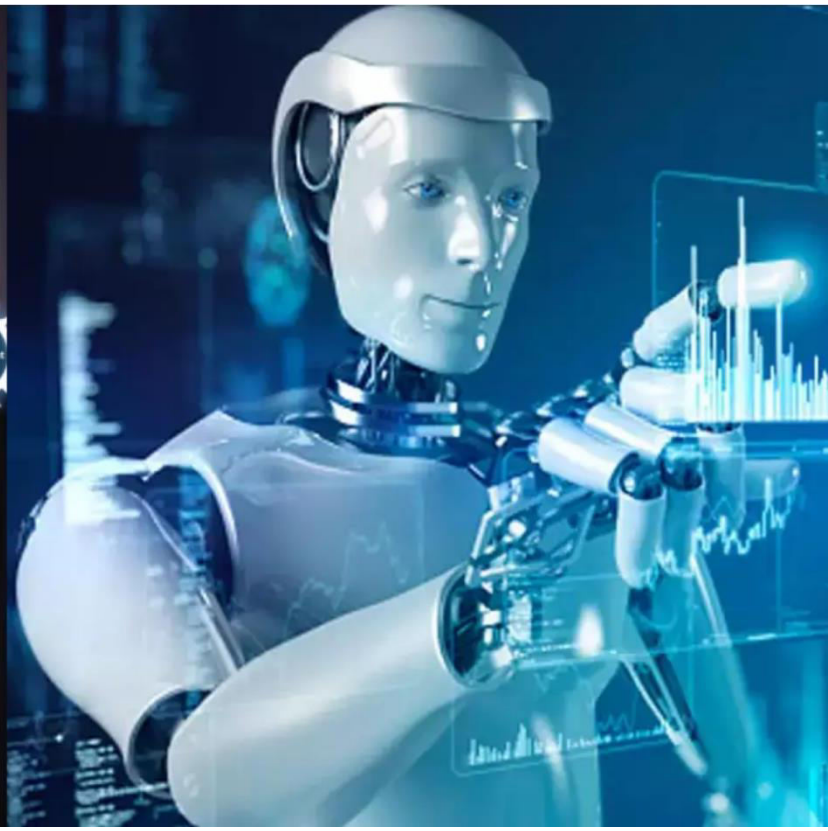

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Safebite AI: AI-Powered Pesticide Risk Detection Using MobileNetV2

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ABSTRACT: SafeBite is a mobile based food safety system developed to estimate pesticide contamination risk on mango fruit using computer vision and deep learning. The proposed system uses MobileNetV2 with transfer learning to classify mangoes into four contamination risk categories: Clean, Low Risk, Moderate Risk, and High Risk. Due to the absence of real contaminated datasets, synthetic pesticide-like residue patterns were generated using OpenCV-based image simulation techniques such as Gaussian blur, alpha blending, spray streak simulation, and desaturation. Albumentations-based augmentation improved the robustness of the model under varying lighting, blur, and orientation conditions. The model was trained using PyTorch and exported into ONNX format for deployment through FastAPI and Flutter mobile integration. Experimental results showed high classification accuracy and strong recall for high-risk contamination detection, demonstrating the feasibility of AI-based visual pesticide screening systems.

KEYWORDS: Text detection, Inpainting, Morphological operations, Connected component labellin MobileNetV2, Deep Learning, Transfer Learning, Computer Vision, Pesticide Detection, OpenCV, ONNX, FastAPI, Flutter.

I. INTRODUCTION

Food safety has become one of the major global concerns due to the excessive use of pesticides in modern agriculture. Fruits and vegetables are frequently sprayed with chemical pesticides to improve productivity and prevent crop damage caused by insects and diseases. However, improper pesticide usage and excessive residue on fruits can create serious health problems for consumers. Long-term exposure to pesticide contaminated food may lead to respiratory disorders, hormonal imbalance, skin allergies, neurological diseases, and chronic toxicity.

Traditional pesticide detection methods rely on laboratory-based chemical analysis techniques such as Gas Chromatography-Mass Spectrometry (GC-MS) and High-Performance Liquid Chromatography (HPLC). Although these methods provide highly accurate results, they are expensive, time-consuming, and inaccessible to ordinary consumers. Most consumers cannot determine whether a fruit contains harmful pesticide residue before consumption.

Recent advancements in Artificial Intelligence (AI), Deep Learning, and Computer Vision have enabled the development of intelligent food quality assessment systems. Convolutional Neural Networks (CNNs) have shown excellent performance in image classification tasks such as fruit quality detection, disease identification, and agricultural monitoring. Lightweight architectures such as MobileNetV2 allow real-time deployment on mobile devices with limited computational resources.

The proposed SafeBite AI system is designed as a mobile-based visual pesticide risk screening solution. Users can capture an image of a mango using a smartphone camera, and the system estimates pesticide contamination risk using deep learning-based image analysis. The system classifies mangoes into four categories:

- Clean
- Low Risk
- Moderate Risk
- High Risk

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One of the biggest challenges faced during development was the absence of publicly available contaminated mango datasets. To overcome this problem, synthetic pesticide residue simulation techniques were developed using OpenCV. These techniques generated realistic contamination patterns such as whitish residue patches, chalky coatings, spray streaks, and surface desaturation effects.

The major objective of this project is to develop an efficient, lightweight, and deployable AI model capable of identifying visual surface anomalies that may indicate pesticide contamination.

II. LITERATURE REVIEW

Several research studies have explored the use of computer vision and deep learning in agriculture and food safety applications. Traditional pesticide residue detection systems primarily rely on laboratory chemical analysis methods. Although these methods provide highly accurate results, they require expensive equipment, laboratory infrastructure, and trained professionals. Due to these limitations, researchers have started investigating image-processing-based alternatives for rapid and low-cost food inspection systems.

Deep Learning-based image classification systems have shown remarkable success in agricultural applications such as fruit disease detection, crop classification, and food quality monitoring. Convolutional Neural Networks (CNNs) automatically extract important image features without requiring manual feature engineering.

MobileNetV2 is one of the most widely used lightweight CNN architectures for mobile applications. It utilizes depthwise separable convolutions and inverted residual blocks to reduce computational complexity while maintaining high classification accuracy. Transfer Learning has also become an important technique for small datasets. Instead of training a model from scratch, pretrained models such as MobileNetV2 reuse previously learned image features from large datasets like ImageNet.

- **AI-Based Crop Disease Detection Using Deep Learning by S. K. Sharma and A. Varma (2021)** developed CNN-based models to classify plant diseases from leaf images and achieved high accuracy for image-based crop health monitoring.
- **Low-Cost Image Processing Techniques for Pesticide Residue Detection by L. Wang and Y. Zhang (2021)** utilized standard RGB cameras along with texture analysis, contrast enhancement, and thresholding methods to detect surface changes caused by pesticide residue layers.
- **Cloud-Based Food Safety Analysis Using AI by K. Dasgupta and R. Rao (2021)** proposed a cloud connected AI system capable of analyzing food images to detect defects and provide instant food safety and washing recommendations to consumers.
- **AI in Fruit and Vegetable Classification by R. Patel and A. Verma (2020)** developed a CNN-based classification system using color, shape, and texture features, achieving improved performance compared to traditional classification approaches.
- **Spectrophotometric Analysis for Pesticide Residue Detection by P. Singh and D. Joshi (2018)** designed a laboratory-based residue detection method and highlighted the limitations of traditional testing methods for rural and real-time applications, motivating the development of portable AI-based alternatives.

However, limited research has been conducted specifically for visual pesticide contamination risk estimation using smartphone-based image analysis. Most existing systems either focus on disease classification or laboratory residue analysis.

The proposed SafeBite AI system attempts to bridge this gap by developing a lightweight and deployable pesticide risk screening framework using synthetic contamination simulation, deep learning, and mobile deployment technologies.

III. PROBLEM STATEMENT

The major challenge in pesticide detection research is the absence of publicly available contaminated fruits dataset. Real pesticide-contaminated mango images are difficult to collect because controlled pesticide application requires laboratory safety protocols and agriculture testing environments.

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Initially, the project contained only 2,000 clean mango images and zero contaminated samples. Training a deep learning classifier using only one class is impossible because the model cannot learn contamination patterns.

To solve this problem, synthetic pesticide simulation techniques were developed using OpenCV. The generated contamination patterns visually imitate real pesticide residue observed during agricultural inspection.

The simulation process generated:

- Whitish residue patches
- Spray streak patterns
- Surface desaturation
- Chalky coating texture

These synthetic contamination patterns allowed the creation of a four-class pesticide risk dataset suitable for deep learning training.

IV. PROPOSED METHODOLOGY

The SafeBite AI system follows a six-stage pipeline:

1. Synthetic Dataset Simulation
2. Data Augmentation
3. Dataset Loading
4. Model Training
5. Model Evaluation
6. Deployment

4.1 Synthetic Dataset Simulation

The first stage involved generating synthetic pesticide contamination patterns using OpenCV-based image processing techniques.

The dataset structure is shown below:

```
dataset/raw/
├── clean/
├── low_risk/
├── moderate_risk/
└── high_risk/
```

Dataset Distribution:

Class	Number of Images
Clean	2,000
Low Risk	4,000
Moderate Risk	4,000
High Risk	4,000
Total	14,000

Table 1. Synthetic Dataset Simulation

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1. Low Risk Simulation

Low Risk images were generated using faint elliptical residue patches with low transparency values.
The following operations were applied:

- Random ellipse generation
- Gaussian blur
- Alpha blending
- Low-intensity noise

2. Moderate Risk Simulation

Moderate Risk images included:

- 3–6 medium-sized residue patches
- Surface desaturation
- Increased opacity
- Texture irregularities

Desaturation shifts fruit color toward grey to simulate pesticide coating effects.

3. High Risk Simulation

High Risk images contained:

- Large overlapping chalky coating
- Directional spray streaks
- Strong desaturation
- Heavy Gaussian noise

OpenCV functions used:

- cv2.ellipse()
- cv2.GaussianBlur()
- cv2.line()

These effects simulated realistic pesticide spraying patterns.

4.2 Dataset Augmentation

The Albumentations library was used to improve robustness under real-world conditions.
Augmentation Techniques:

Technique	Purpose
Horizontal Flip	Orientation variation
Vertical Flip	Angle variation
Rotation	Camera tilt simulation
Brightness/Contrast	Lighting variation
CLAHE	Contrast enhancement
Gaussian Noise	Sensor noise simulation
Grid Distortion	Curved fruit surface simulation
Random Crop	Zoom variation
Coarse Dropout	Occlusion simulation

Table 2. Dataset Augmentation techniques

After augmentation, the dataset size increased from 14,000 to approximately 60,000 images.

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Final Augmented Dataset:

Class	Images
Clean	13,000
Low Risk	13,000
Moderate Risk	13,000
High Risk	13,000

Table 3. Augmented Dateset Count

4.3 **Dataset Loading**
dataset/augmented/

├── clean/ → label 0

├── low_risk/ → label 1

├── moderate_risk/ → label 2

└── high_risk/ → label 3

The dataset was divided into:
- Training = 80%
- Validation = 10%
- Testing = 10%

ImageNet normalization values were applied because MobileNetV2 was pretrained on ImageNet.
ImageNet normalization values:
mean = [0.485, 0.456, 0.406]
std = [0.229, 0.224, 0.225]

4.4 Synthetic Dataset Simulation
MobileNetV2 was selected because of:
- Lightweight architecture
- Fast inference speed
- Low memory usage
- Mobile deployment compatibility

MobileNetV2 Specifications:

Parameter	Value
Parameters	3.4 million
Input Size	224 × 224
Framework	PyTorch
Deployment	ONNX Runtime

Table 4. Specifications of MobileNetV2

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The architecture uses:
- Inverted Residual Blocks
- Depth wise Separable Convolutions
- Skip Connections

4.5 Transfer Learning Strategy
Transfer Learning was implemented in two phases.

Phase 1 — Frozen Backbone
- Backbone layers frozen
- Only classification head trained
- Learning Rate = 1e-3

Phase 2 — Fine-Tuning
- Top layers unfrozen
- Fine-tuning performed
- Learning Rate = 1e-4

Custom classification head:
Dropout (0.4)
Linear (1280 → 256)
ReLU ()
Dropout (0.2)
Linear (256 → 4)

4.5 Loss Function Optimizer
Weighted Cross Entropy Loss was used to address class imbalance in the four-class pesticide risk dataset. The Adam optimizer was used for training.

Advantages of Adam:
- Faster convergence
- Stable optimization
- Adaptive learning rates

Learning rate scheduling:
- StepLR during Phase 1
- CosineAnnealingLR during Phase 2

V. RESULTS AND DISCUSSION

The model was evaluated using:
- Accuracy
- Precision
- Recall
- F1 Score
- Confusion Matrix

The most important metric was Recall for the High-Risk class because missing contaminated fruit is dangerous.
Confusion Matrix:

Actual / Predicted	Clean	Low	Moderate	High
Clean	950	30	15	5

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Low Risk	25	880	70	25
Moderate Risk	5	40	890	65
High Risk	2	8	45	945

Table 5. Confusion Matrix for Pesticide Risk Classification

The result showed:
- Strong High-Risk detection
- Minimal false negatives
- High classification performance

The model successfully detected:
- Whitish residue
- Spray streaks
- Chalky coatings
- Surface discoloration

Data augmentation improved performance under:
- Different lighting
- Camera blur
- Rotation
- Zoom variation
- Occlusion

VI. DEPLOYMENT

The trained PyTorch model was exported into ONNX format for lightweight inference

Deployment Pipeline

Flutter App
↓
FastAPI Backend
↓
Image Preprocessing
↓
ONNX Runtime
↓
Prediction Output

Technologies Used

Component	Technology
Frontend	Flutter
Backend	FastAPI
Model Framework	PyTorch
Deployment Format	ONNX
Inference Engine	ONNX Runtime

Table 6. Implementation Technologies

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The Flutter application captures mango images and sends them to the FastAPI backend through HTTP requests. The backend preprocesses the image into 224×224 format and performs inference using the ONNX model.
The final prediction is returned as JSON response data.

Output Screens:

Fig. 1. SafeBite Splash Screen

Fig. 2. Language Selection Interface

Fig. 3. SafeBite Home Interface

Fig. 4. Scanning Interface

VII. LIMITATIONS

Although SafeBite AI provides efficient visual pesticide screening, it has several limitations.
Technical Limitations

- Cannot detect invisible pesticide contamination
- Performance decreases with blurry images
- Synthetic contamination may not perfectly match real contamination
- Natural blemishes may trigger false positives
- Only trained on mango datasets

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Ethical Considerations

- False confidence risk
- False alarm risk
- Not clinically validated
- Should not replace laboratory testing

VIII. FUTURE SCOPE

Future improvements may include:

- Real pesticide contamination datasets
- Multi-fruit support
- Hyperspectral imaging integration
- Real-time edge AI deployment
- Laboratory validation
- Cloud-based monitoring systems

The integration of hyperspectral imaging and chemical sensor fusion may significantly improve contamination detection accuracy.

IX. CONCLUSION

SafeBite AI demonstrates the practical application of Artificial Intelligence, Computer Vision, and Deep Learning in food safety systems. The project successfully combines OpenCV simulation, Albumentations augmentation, MobileNetV2 transfer learning, and ONNX deployment into a lightweight and deployable mobile solution. The proposed system provides an affordable and accessible method for estimating pesticide contamination risk using smartphone-based image analysis. Although the system does not replace laboratory chemical testing, it serves as a valuable first-level screening tool for consumers. The project highlights the potential of AI-powered food safety applications in modern agriculture and public health awareness systems.

X. ACKNOWLEDGEMENT

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