

# Home Safe: AI-Powered Anomaly Detection for Housing Inspection

Dr. Amrapali Chavan<sup>1</sup>, Soham Sakunde<sup>2</sup>, Aditya Shelake<sup>3</sup>, Swapnil Sable<sup>4</sup>, Vaishnav Sakore<sup>5</sup>

<sup>1</sup>Amrapali Chavan, Computer Engineering & AISSMS IOIT, Pune, India
<sup>2</sup>Soham Sakunde, Computer Engineering & AISSMS IOIT, Pune, India
<sup>3</sup>Aditya Shelake, Computer Engineering & AISSMS IOIT, Pune, India
<sup>4</sup>Swapnil Sable, Computer Engineering & AISSMS IOIT, Pune, India
<sup>5</sup>Vaishnav Sakore, Computer Engineering & AISSMS IOIT, Pune, India

**Abstract** - This paper presents HomeSafe, an AI-driven system for automated housing inspection using Machine Learning-based anomaly detection. The system detects structural cracks from images and estimates their severity, providing detailed reports for decision-making. A MobileNetV2-based CNN model is fine-tuned for crack detection, achieving high accuracy on a benchmark dataset. The system further estimates crack width and dimen sions using image processing techniques. A webbased interface (Streamlit) is developed for easy image uploads and report generation. The project aims to assist engineers, homeowners, and real estate professionals in conducting automated building inspections.

*Key Words*: Crack Detection, Deep Learning, Anomaly De tection, CNN, MobileNetV2, Image Processing, Streamlit, Hous ing Inspection.

# **1. INTRODUCTION**

Structural integrity assessment is a critical aspect of building safety and maintenance. Ensuring the safety of residential buildings is essential to prevent potential hazards caused by structural degradation. Traditional inspection methods require manual experienced professionals to conduct thorough eval uations, making the process time-consuming, subjective, and costly. Moreover, manual inspections are prone to human error and inconsistencies, leading to unreliable assessments that may overlook subtle but significant defects. Advancements in AI and computer vision have enabled automated solutions that serve as efficient alternatives to traditional inspection methods. Deep learning techniques, par ticularly Convolutional Neural Networks (CNNs), have shown remarkable accuracy in detecting structural defects such as cracks. By leveraging AI-driven anomaly detection, it is possi ble to streamline the crack detection process, reduce inspection costs, and provide objective, data-driven insights into structural health. This project introduces HomeSafe, an AI-powered tool designed to automate housing inspections using deep learning and image processing. The system is built on a MobileNetV2 based CNN model, trained to detect cracks and assess their severity. Image processing algorithms are used to estimate crack width and dimensions, enhancing inspection reliability. A user-friendly Streamlit web interface enables engineers, homeowners, and professionals to upload images and generate detailed reports.

#### 2. RELATED WORK

- A. Deep Learning in Crack Detection Previous studies have shown CNN-based models perform well for crack detection, including architectures like ResNet, VGG, and MobileNet [1].
- **B.** Image Processing for Crack Measurement Techniques like Canny edge detection [7] and contour analysis are used to estimate crack dimensions.
- C. Existing Commercial Solutions Many commercial tools rely on manual or semiautomated techniques, which our system aims to enhance with end-to-end automation.

#### **3. PROBLEM STATEMENT**

• Manual inspections are expensive and inefficient.

• There is no automated tool to both detect cracks and assess their severity.

• Homeowners and engineers lack accessible tools for quick inspection reports.

**Solution:** HomeSafe automates the crack detection process, measures crack dimensions, and generates severity reports through a user-friendly interface.

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# 4. SYSTEM ARCHITECTURE

# A. Overall Architecture

1) Image Input: User uploads a structural image.

2) Preprocessing: Images are resized and normalized for crack detection.

3) Anomaly Detection Model: MobileNetV2 classifies cracked vs. non-cracked.

4) Crack Measurement Module: Uses edge detection and contour analysis.

5) Severity Analysis Module: Categorizes cracks.

6) Web Interface: Built using Streamlit [4].

# B. Model Architecture

- MobileNetV2-based Transfer Learning [1]
- Canny Edge Detection [7]
- Contour Analysis for Width Estimation

# C. System Flow Diagram

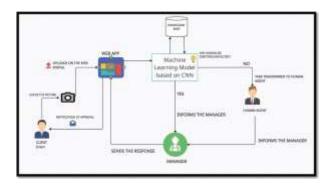


Fig -1: System Flow Diagram of the HomeSafe Model

# 5. METHODOLOGY

#### A. Data Preprocessing

- Dataset: Crack Non-Crack Images from SDNET2018 [2].
- Image Augmentation: Rotation, Scaling, Flipping
- Image Size: 224×224 pixels

# 6. IMPLEMENTATION

# A. Model Training

- Pre-trained MobileNetV2 (ImageNet)
- Fine-tuned for crack classification
- Batch Size: 32, Epoch: 20
- Optimizer: Adam (lr = 0.0001)
- Loss: SparseCategoricalCrossentropy

#### B. Email Report Functionality

- Report includes severity level, crack length/width, and recommendations.
- Sent via email with SMTP using Streamlit Secrets.
- Attachments: Original and edge-detected images.

# C. Web Application Development

- Backend: Python with gdown and OpenCV [3]
- Frontend: Streamlit [4].
- Model (>100MB) loaded from Google Drive
- GitHub Actions script keeps Streamlit app awake

# 7. EXPERIMENTAL RESULTS

#### A. Datasets

- SDNET2018 Crack Dataset [2]
- Benchmark Structural Images

#### **B.** Performance Metrics

#### TABLE I

#### PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1 Score
HomeSafe	95.6%	94.5%	96.2%	95.3%

#### 8. CHALLENGES AND LIMITATIONS

- Crack appearance varies widely by surface and lighting.
- High-res images needed for precise dimension measure ment.
- More diverse datasets would boost generalization.



# 9. APPLICATIONS

- Automated structural health reports.
- Property assessments and valuation.
- Preventive infrastructure monitoring

# **10. FUTURE WORK**

- Add multi-scale and 3D depth crack detection.
- Improve UI for field usability.
- Extend dataset to cover more surface types

# **11. CONCLUSION**

HomeSafe is a reliable AI-based solution for automated housing inspection. It integrates deep learning with image pro cessing and web deployment to generate real-time structural analysis reports.

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