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AI-Driven Detection of Moisture Issues in Buildings Using Convolutional Neural Networks

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Abstract:- This study presents the development and application of a Convolutional Neural Network (CNN) model for the detection and classification of moisture-related issues in buildings, specifically focusing on leakage, seepage, and dampness. The study highlights the challenges faced in data acquisition, including the similarities in visual characteristics of different moisture issues and the limitations posed by varying lighting conditions and image quality. A high-resolution mobile camera was employed to capture images, which were then processed using a CNN model. The results demonstrate the model's accuracy and reliability, with an overall classification accuracy of 94%.

Keywords*: CNN, Moisture Detection, Leakage, Seepage, Dampness, Buildings, Image Processing, Deep Learning, High-Resolution Imaging, Classification Accuracy.*

1. Introduction

Moisture-related issues in buildings have significant implications, as they account for 75-80% of building envelope defects, according to WHO guidelines on indoor air quality [55]. Almas et al. also found that moisture is responsible for 76% of building defects [28], with repair costs ranging from 2.4% to 3.15% of total construction expenses, as noted by Alomari [29]. The economic impact is evident in the U.S., where dampness and mold contribute to 21% of asthma cases, costing $3.5 billion annually [55].

Building susceptibility to moisture problems like seepage and dampness is influenced by various factors, including climate and construction practices, as stated by the National Institute of Building Sciences (NIBS) [56]. The ASHRAE Handbook identifies contributors such as inadequate drainage, specific construction materials, high humidity, and poor ventilation [57]. The National Building Code of Canada (NBC) emphasizes that water-related issues threaten structural integrity, occupant health, and property value, necessitating timely detection [58].

Traditional detection methods, while effective, often rely on visual inspections and manual monitoring [58]. However, modern sensor instruments like moisture meters, infrared thermography cameras, and water leak sensors provide non-invasive, accurate moisture detection [59, 30, 38, 31]. AI and ML advancements further enhance detection efficiency and accuracy, offering a proactive approach to identifying and addressing moisture problems in buildings, as highlighted by Baduge and Dombale [39, 40].

1.1 Background and Importance of Moisture Detection

Moisture problems such as leakage, seepage, and dampness are significant concerns in buildings. These issues can lead to structural damage, increased maintenance costs, and potential health hazards such as mold growth. Traditionally, the detection of these issues has relied on manual inspections, which are labor-intensive, time-consuming, and prone to human error.

1.1.1 Leakage

Leakage occurs when water enters a building through external imperfections such as cracks in walls, roofs, or foundations. This can lead to structural damage, mold growth, and material deterioration. Causes include both structural issues, like roof leaks and cracks, and maintenance problems, such as plumbing leaks and poor sealing around windows and doors. To prevent moisture-related issues, regular roof maintenance, sealing cracks, and proper sealing of openings are essential. Mitigation involves repairing damaged roofing, addressing structural cracks, and fixing plumbing issues to protect the building from future water intrusion.

Figure 1. 1 - Leakage Images

1.1.2 Seepage

Seepage is the slow infiltration of water through porous materials like soil, concrete, or masonry, often going unnoticed until it causes significant damage. It can weaken structural integrity, lead to mold growth, and result in dampness that damages walls and floors. Causes include elevated groundwater levels, inadequate waterproofing, structural defects, and poor drainage systems. Seepage can lead to issues like efflorescence, damp patches, and material deterioration, especially during freeze-thaw cycles. Prevention requires effective waterproofing, proper drainage, and high-quality construction materials. Mitigation involves sealing seepage paths, improving drainage, reinforcing waterproofing, and monitoring groundwater levels to avoid further damage.

Figure 1. 2 - Seepage Images

1.1.3 Dampness

Figure 1. 3 - Dampness Images

Dampness occurs due to excessive moisture or high humidity within a building, often caused by leaks, poor ventilation, or inadequate insulation. It can manifest as visible moisture on walls, floors, or ceilings, often accompanied by musty odors and mold growth. Key factors include leaks, seepage, condensation, and moisture from indoor activities. Dampness can lead to health risks, such as respiratory issues, and cause structural damage, including decay, rot, and instability, especially in wooden structures. Prevention involves improving ventilation, using proper insulation, and controlling moisture sources. Mitigation includes enhancing airflow, upgrading insulation, installing moisture barriers, and repairing indoor moisture sources to protect both the building and its occupants.

2. Methodology

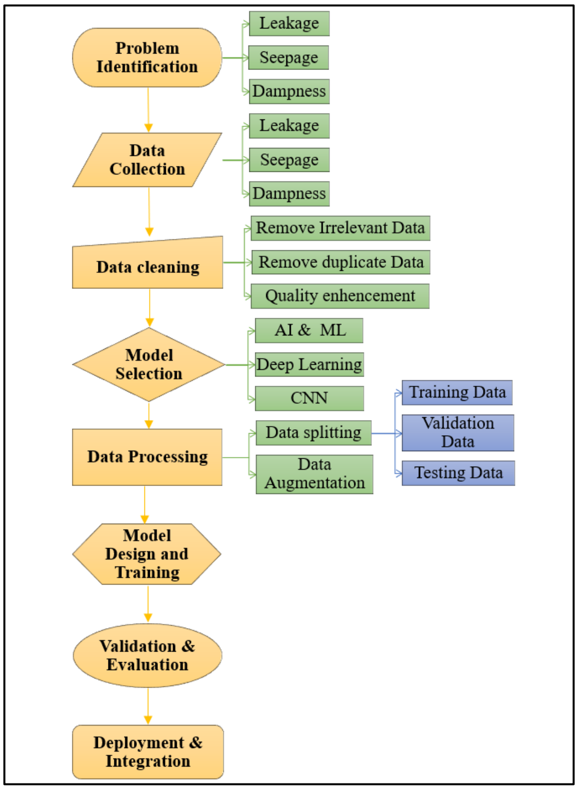


Figure 2. 1 - Methodology flow chart

2.1 Problem identification

The process of addressing moisture issues in buildings starts with collecting reports and observations from occupants to identify visible signs of leakage, seepage, and dampness. A preliminary site inspection follows to detect common indicators such as water stains and peeling paint. Historical data on construction, renovations, and weather conditions is reviewed to understand past water ingress issues and environmental influences. The investigation then focuses on identifying sources of moisture, evaluating construction materials, and categorizing potential problems. A comprehensive report is prepared, outlining findings, causes, and preliminary recommendations. This systematic approach ensures a thorough understanding of moisture problems and supports the development of effective long-term solutions.

2.2 Data Collection

To train a model for detecting water-related issues in buildings, high-resolution images were collected from various surfaces, including walls, ceilings, and floors. The dataset includes 20 images of leakage, 126 of seepage, and 298 of dampness, all captured under consistent lighting and angles to ensure uniform quality. Images were carefully annotated with labels and bounding boxes to indicate the type and severity of damage. This thorough and organized data collection provides a strong foundation for training an accurate and effective model for water damage detection.

2.2.1 Leakage sample images

Figure 2. 2 - Leakage sample images

2.2.2 Seepage sample images

Figure 2. 3 - Seepage sample images

2.2.3 Dampness sample images

Figure 2. 4 - Dampness sample images

2.3 Data Cleaning

Data cleaning involves reviewing and refining the collected images by removing redundant or irrelevant data to maintain a focused dataset. Redundant images are eliminated to avoid repetition, and irrelevant images are filtered out to ensure the model only learns from informative data. Quality enhancement techniques such as adjusting brightness, contrast, and noise reduction are applied to improve image clarity.

Following data cleaning, annotation is performed, categorizing images by the type (leakage, seepage, dampness). Bounding boxes or segmentation masks are used to precisely highlight damaged areas, facilitating accurate model training for effective water damage detection.

2.4 Model selection

For this study using a Convolutional Neural Network (CNN) to improve the detection and analysis of dampness, leakage, and seepage in buildings. This approach employs advanced deep learning techniques to automate and enhance the accuracy of monitoring building conditions. Unlike traditional inspection methods that depend on manual analysis and can be both slow and error-prone, the CNN model is trained on a diverse set of images that depict various moisture-related issues. By learning to recognize and differentiate between different types of damage through complex pattern analysis, the CNN can effectively process new images from inspections or surveillance systems. This allows for real-time detection and classification of moisture problems, leading to more efficient and accurate monitoring, timely interventions, and better maintenance strategies.

2.4.1 CNN Model Architecture

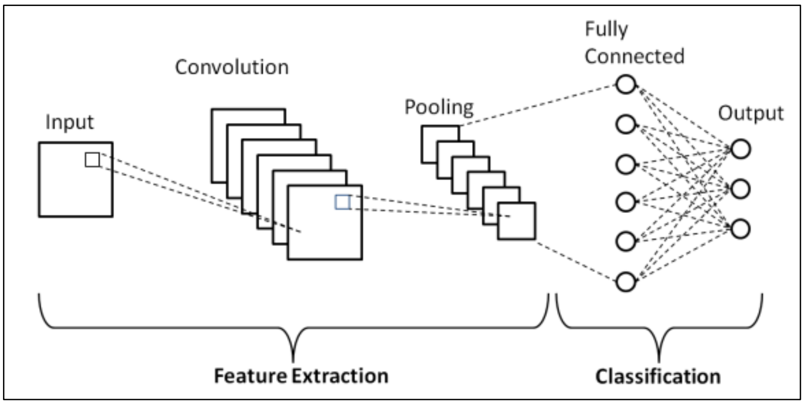


Figure 2. 5 - CNN key components

CNNs are feedforward networks where information flows from input to output, inspired by the visual cortex of the brain. For building applications, CNNs are commonly used for tasks like identifying maintenance issues through image classification. The architecture includes the following key components:

1. **Input Layer**: Receives raw image data, organizing it for further processing. Images are typically preprocessed to uniform dimensions and normalized before entering the network.
2. **Convolutional Layers**: Extract features by applying filters to the input images. These layers detect patterns like leaks or structural flaws, creating activation maps that highlight important features.
3. **Pooling Layers**: Reduce the spatial resolution of feature maps, retaining essential information while lowering data size and computational demands. Max pooling is commonly used to emphasize the most significant features.
4. **Fully Connected Layers**: Perform high-level inference by combining features extracted in previous layers, leading to the final prediction. They are essential for tasks like classifying water damage or structural defects.
5. **Output Layer**: Converts the network's processing into final predictions or classifications. For classification tasks, softmax is used to output probabilities for each class, providing actionable insights for building analysis.

This structured approach ensures that CNNs efficiently detect and classify issues in, supporting timely maintenance and repairs.

2.5 Data Processing

Data processing begins by dividing the dataset into training, validation, and test sets to ensure balanced and accurate model training. The training set, comprising 80-90% of the original data, is used to teach the model to recognize water-related issues. The validation set, accounting for 10-20% of the augmented training data, helps fine-tune the model's parameters, ensuring it generalizes well to unseen data. The test set, also 10-20% of the original data, is reserved for the final evaluation, providing an unbiased measure of the model's performance.

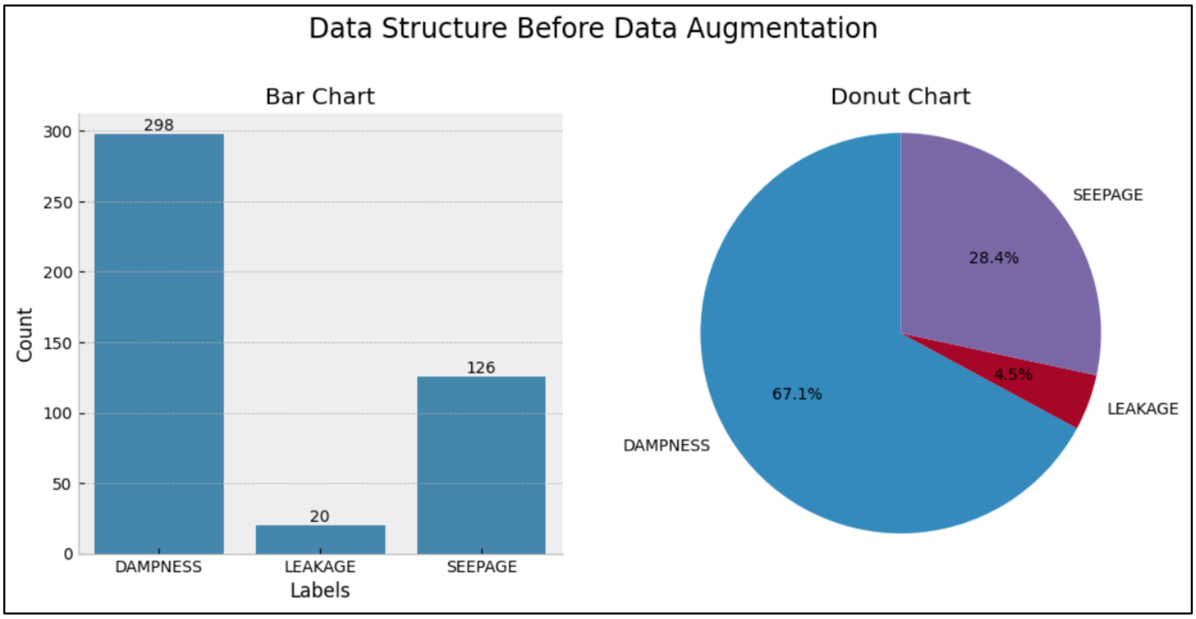


Figure 2. 6 – Data structure before data augmentation

To increase the model's robustness, data augmentation techniques such as rotation and brightness adjustments are applied, expanding each category (leakage, seepage, dampness) to 500 samples. Proper documentation and organization of this process are critical for replicating the work and validating results. This thorough preparation enhances the model's accuracy and reliability in detecting water-related issues in building images.

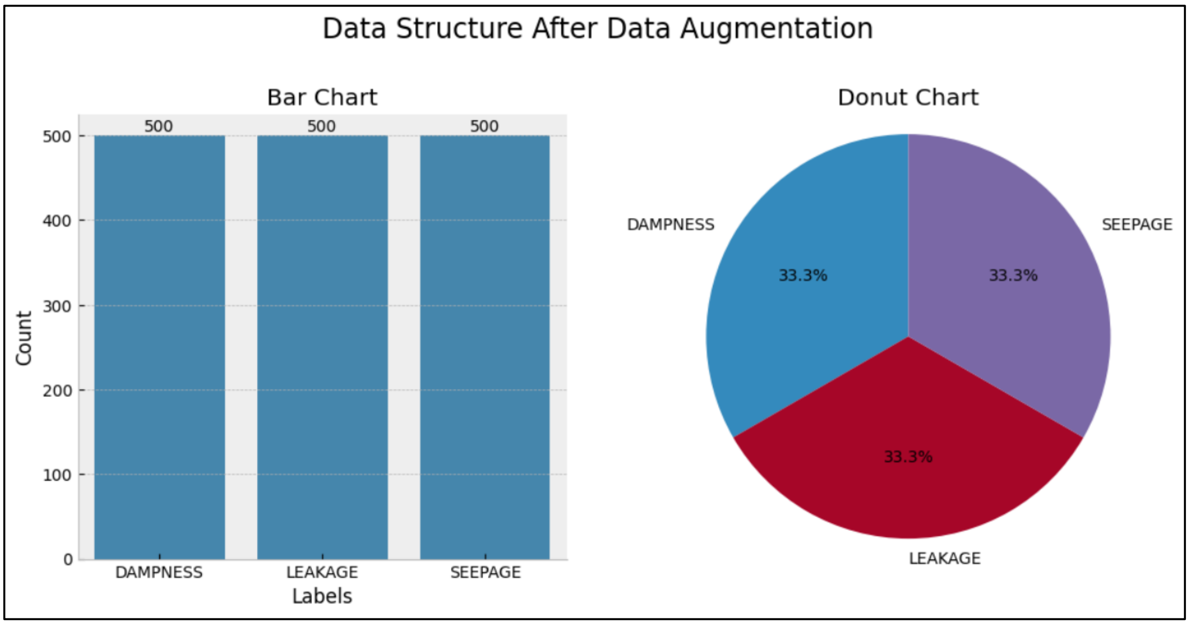
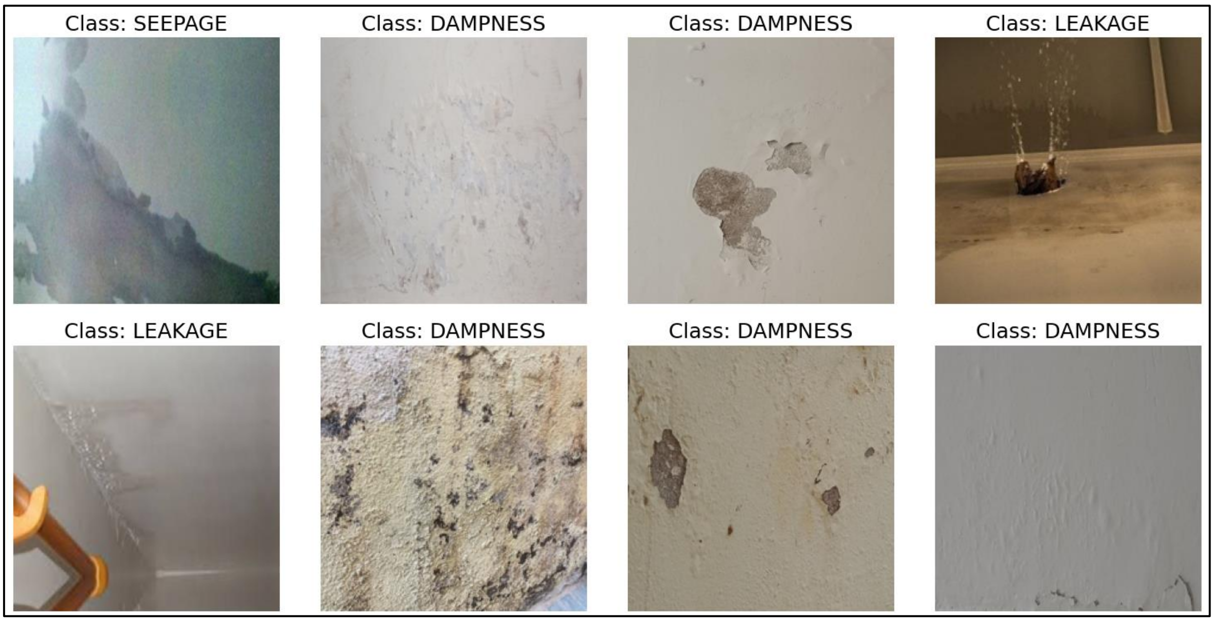


Figure 2. 7 – Data structure after data augmentation

2.6 Model Design and Training

A Convolutional Neural Network (CNN) was chosen for its ability to analyze visual data and detect issues like water leakage, seepage, and dampness in building images. The model was trained on an augmented dataset, which included a variety of examples to improve generalization. Normalization was applied to ensure consistency in inputs, stabilizing the training process.

Training involved adjusting the model's weights using a loss function and an optimizer, with careful control of the learning rate. The model's performance was monitored using a validation set to prevent overfitting, and early stopping was implemented to end training when improvement ceased. The final model's accuracy and precision were assessed, confirming its effectiveness in detecting water-related issues in building images.



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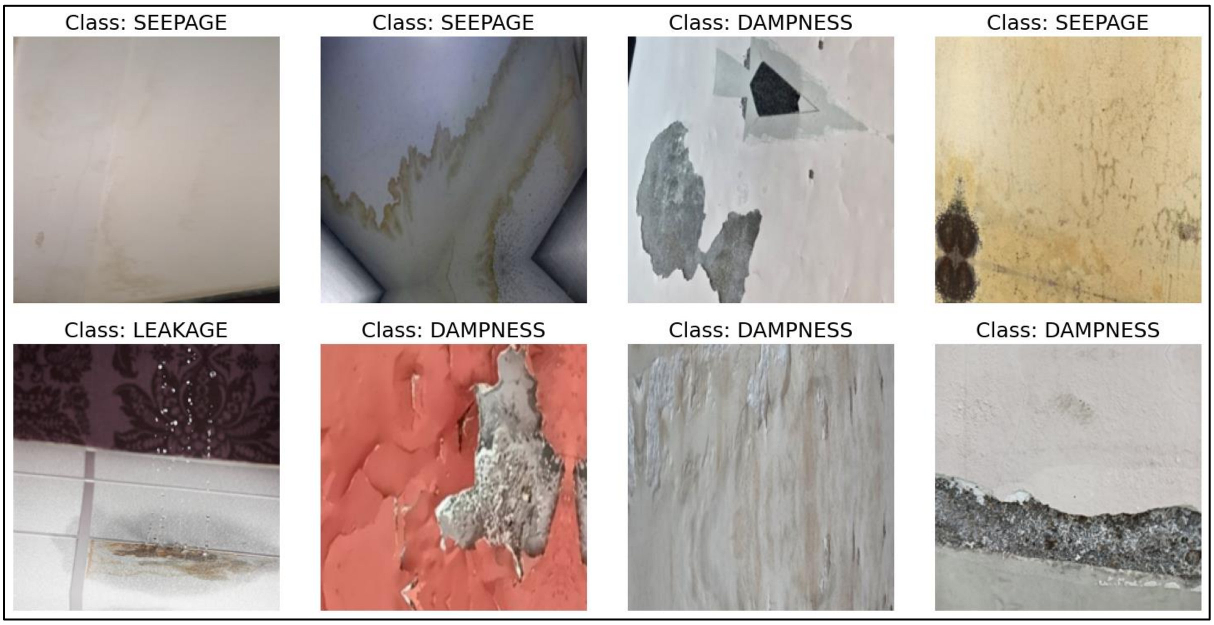

Figure 2. 8 – Visual data of detected issues

2.7 Validation and Evaluation

After training, the model was validated to fine-tune hyperparameters and ensure it generalizes well. Metrics such as accuracy, precision, recall, and F1-score were monitored to detect any signs of overfitting or underfitting. Adjustments were made as needed to enhance performance.

The final evaluation was conducted on a reserved test set to assess the model's ability to generalize to new data. Performance metrics confirmed the model's accuracy and reliability in detecting water-related issues in building images, indicating its readiness for practical application.

2.8 Deployment and Integration

The successful deployment of a trained CNN model for managing moisture issues in buildings requires a well-structured approach. This begins with selecting a suitable platform, whether web-based or desktop, that can accommodate various user needs and deployment scenarios. Integrating the CNN model into the user interface is essential for effective user interaction. The interface should allow easy image uploads and provide real-time feedback, making the model's results accessible and understandable to users with varying levels of technical expertise. This integration enhances the user experience by streamlining the process of detecting and addressing moisture issues in buildings.

3. Results and Discussion

CNNs, inspired by human visual perception, are powerful tools for image recognition tasks. Their ability to learn and extract features from raw pixel data makes them effective for detecting moisture-related issues such as dampness, leakage, and seepage in buildings.

3.1 Classification Report of CNN:

	precision	recall	f1-score	support
DAMPNESS	0.92	0.91	0.91	100
LEAKAGE	0.95	0.98	0.97	100
SEEPAGE	0.94	0.92	0.93	100
accuracy			0.94	300
macro avg	0.94	0.94	0.94	300
weighted avg	0.94	0.94	0.94	300

Figure 3. 1 - Classification Report of CNN

The CNN model for detecting dampness, leakage, and seepage in buildings was evaluated using precision, recall, F1-score, and support metrics. The model showed high precision (0.92-0.95) and recall (0.91-0.98) across all categories, with F1-scores indicating a strong balance between precision and recall (0.91-0.97). It achieved an overall accuracy of 94%, with consistent performance across all classes, as reflected by macro and weighted averages of 0.94 for precision, recall, and F1-score. The uniform support values confirm the robustness of the model's performance in detecting moisture issues in buildings.

3.2 Confusion Matrix of CNN:

The confusion matrix highlights the model's classification accuracy, correctly identifying 91 cases of dampness, 98 cases of leakage, and 92 cases of seepage. However, some misclassifications occurred: 5 instances of dampness were misclassified as leakage, and 4 as seepage; 2 instances of leakage were misclassified as seepage; and 8 instances of seepage were misclassified as dampness. Despite these errors, the model demonstrates strong overall accuracy, with opportunities for further refinement.

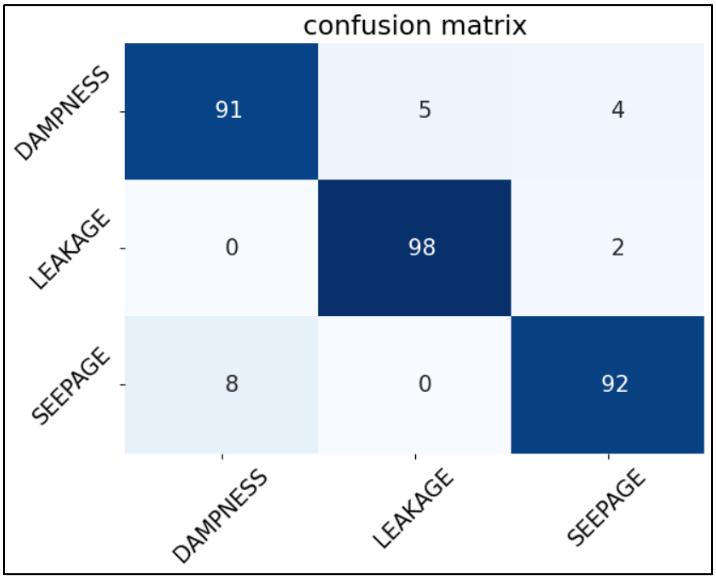

Figure 3. 2 - Confusion Matrix of CNN

3.3 Accuracy Plot Graph of CNN:

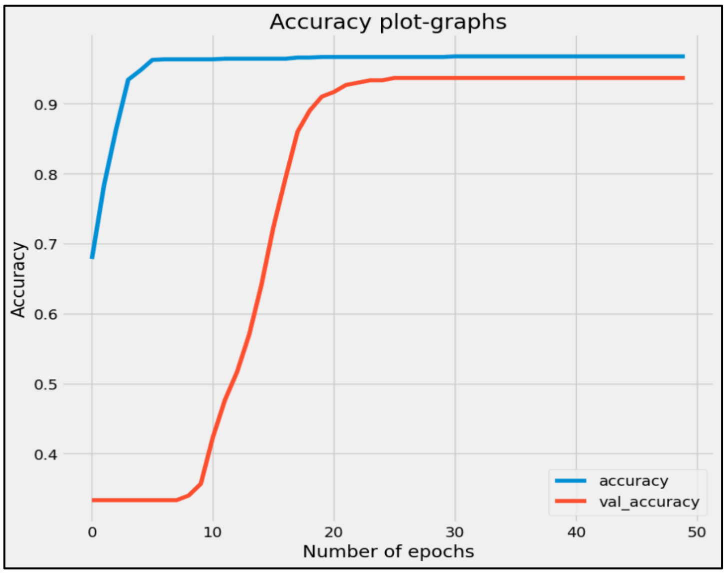

Figure 3. 3 - Accuracy Plot Graph of CNN

The accuracy plot shows rapid improvement in training accuracy, reaching 97.09% after 50 epochs, while validation accuracy plateaus at 93.67%, indicating potential overfitting. To mitigate this, techniques like early stopping and learning rate adjustments are suggested to enhance generalization and improve validation accuracy.

3.4 Loss Plot Graph of CNN:

The loss plot illustrates the model's learning process, with both training and validation losses decreasing over time. The alignment of training and validation losses suggests that the model generalizes well without significant overfitting. Further improvements could be achieved by fine-tuning hyperparameters, though the model already shows reliable performance on both training and validation datasets.

Figure 3. 4 - Loss Plot Graph of CNN

3.5 Web Interface

3.5.1. Login Form:

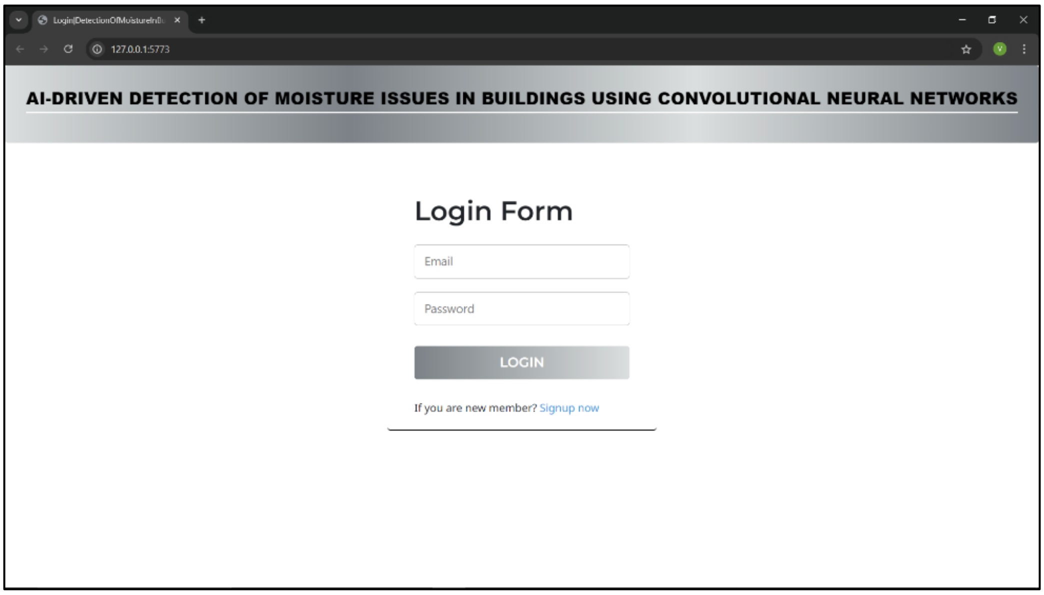

Figure 3. 5 - Login form

Figure 3.5 presents the login page of a Flask web application designed for detecting leakage, seepage, and dampness in buildings using AI and ML. The form allows users to securely input their email and password to access the application.

3.5.2. Image Upload Page:

Figure 3.6 shows the image upload page, where users can select and upload an image from their device for analysis. The AI/ML model processes the image to detect potential moisture issues, providing users with detailed insights based on the visual data.

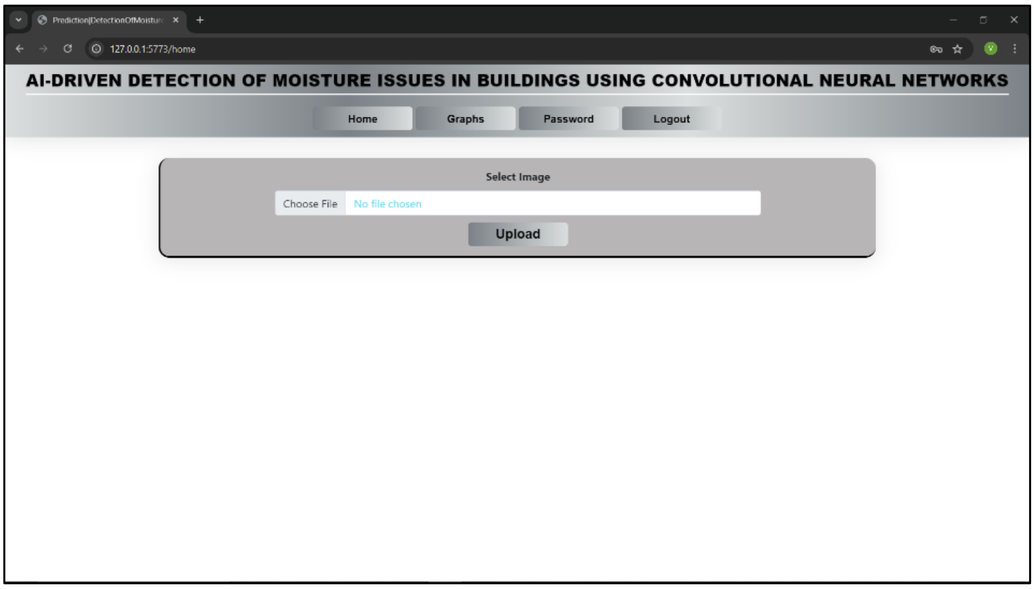

Figure 3. 6 - Image Upload Page

3.5.3. Dampness Detection:

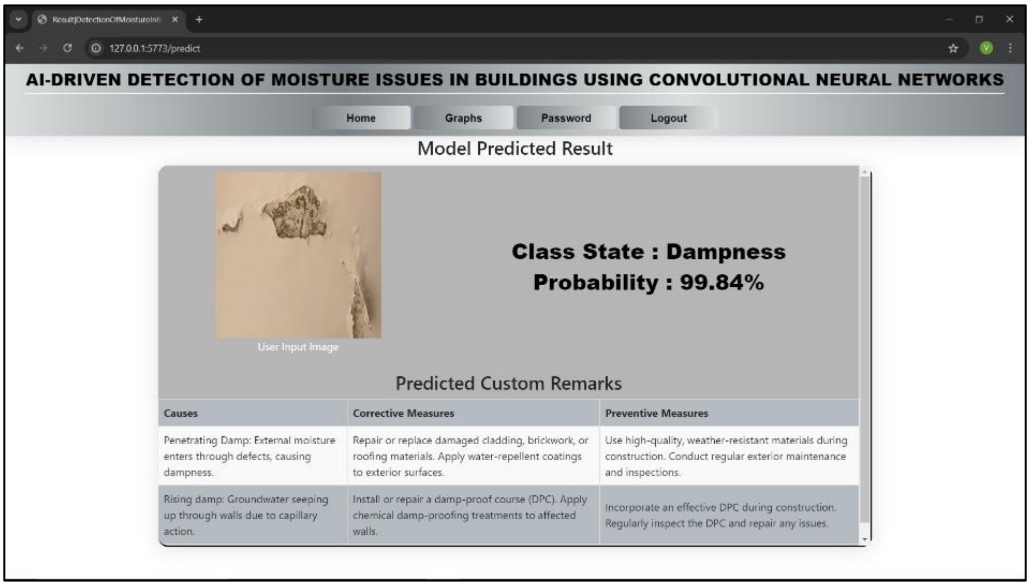

Figure 3. 7 - Dampness detection

Figure 3.7 displays the results page where the uploaded image is analyzed for dampness. The AI model detects dampness with a 99.84% probability. The page includes the analyzed image, possible causes, corrective actions, and preventive measures, offering users practical advice.

3.5.4. Seepage Detection:

Figure 3.8 shows the results page for seepage detection, with the AI model detecting seepage with a 97.80% probability. The page includes the analyzed image and offers insights, corrective actions, and preventive suggestions to manage the issue.

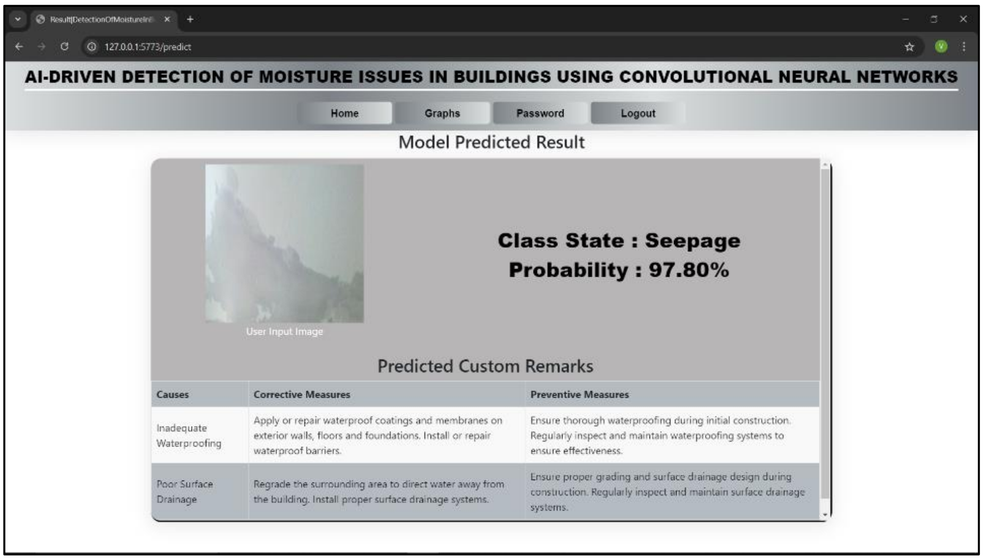

Figure 3. 8 - Seepage detection

3.5.5. Leakage Detection:

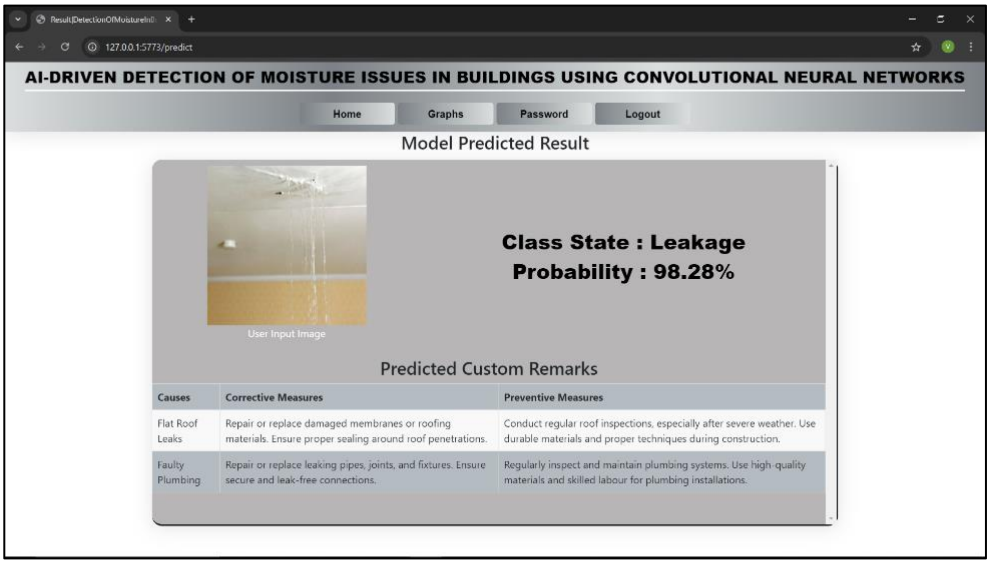

Figure 3. 9 - Leakage detection

Figure 3.9 presents the results page for leakage detection. The AI model identifies leakage with a 98.28% probability. The page provides the analyzed image, insights into leakage causes, suggested corrective actions, and preventive measures to help users address the issue effectively.

4. Conclusions

1. The study faced significant challenges in acquiring clear and accurate pictorial data for issues like leakage, seepage, and dampness. These challenges were mainly due to varying lighting conditions, the complexity of the affected areas, and the necessity for specialized equipment. To address this, a high-resolution mobile camera was utilized, ensuring effective documentation of problem areas.

2. The similarity in the visual signs of leakage, seepage, and dampness often led to confusion during data collection. This overlap in appearance posed difficulties in accurately distinguishing and documenting each type of issue, emphasizing the need for careful analysis.
3. The analysis of the collected data indicated that poor construction practices, failures in waterproofing, and damaged plumbing are the primary causes of leakage, seepage, and dampness. Effective corrective measures include targeted repairs, proper sealing, and enhanced drainage systems, while preventive strategies involve regular maintenance, the use of high-quality materials, and adequate waterproofing techniques
4. To predict moisture problems from pictorial data, a Convolutional Neural Network (CNN) algorithm was selected. This choice was driven by the algorithm's efficiency and its proven capability to process image-based data effectively.
5. In developing the front-end interface for the model, the focus was on user-friendliness, This was aimed to enhance usability of the model.
6. The literature review revealed a gap in existing research, as no papers were found on predictive tools for moisture problems in buildings. This study seeks to address this gap by contributing new insights and aims to publish a journal paper on the subject.

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