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DETECTION AND CLASSIFICATION OF SURFACE DAMAGE IN CONCRETE USING EFFICIENTNET-B1

Priyansh Verma[1], Prof. Abhishek Mishra[2], Prof. Sachin Kumar Singh[3]

[1]*M.Tech Scholar, Department of Civil Engineering, I.E.T Lucknow, India*
[2]*Assistant Professor, Department of Civil Engineering, I.E.T Lucknow, India*
[3]*Assistant Professor, Department of Civil Engineering, I.E.T Lucknow, India*

Abstract - Concrete structures often experience surface-level deterioration due to environmental, mechanical, or chemical exposure. Manual inspection methods for identifying cracks, spalling, and corrosion are labor-intensive and subjective. This paper proposes an automated image-based classification system using EfficientNet-B1, a convolutional neural network model optimized for high performance and low computational cost. A curated dataset of 5032 labeled images across four categories—Healthy, Crack, Spalling, and Rust—was used. Transfer learning was applied, and the model was trained using augmented data in Jupyter Notebook. The trained model achieved an accuracy of 95.4% on the test set, with high precision and recall for all damage classes. These results indicate that EfficientNet-B1 is suitable for real-time concrete surface assessment applications in retrofitting and structural health monitoring.

Key Words: **Concrete Damage, Crack Detection, Spalling, Rust, EfficientNet-B1, Deep Learning, Structural Health Monitoring, Transfer Learning**

1.INTRODUCTION

Concrete is the most extensively used construction material worldwide, favored for its strength, durability, and adaptability. However, surface-level deterioration such as cracking, spalling, and corrosion is inevitable over time. These damages are early indicators of more significant structural distress. Manual inspection remains the primary assessment method but is prone to subjectivity and inefficiency, especially in large-scale infrastructures.

Recent advancements in computer vision and deep learning offer scalable and objective solutions. Convolutional Neural Networks (CNNs) have demonstrated promising performance in detecting and classifying structural defects. However, many conventional CNNs require large datasets and extensive training time, which limits their practical implementation.

This study presents an approach using EfficientNet-B1, a lightweight and scalable CNN model, for the automated classification of concrete surface damage into four categories. The model is trained using transfer learning on a dataset of 5032 labeled images and evaluated using standard metrics like accuracy, precision, recall, and F1-score. The goal is to create a robust, mobile-compatible inspection tool for real-time structural damage assessment.

2. LITERATURE REVIEW

Concrete surface damage detection using deep learning has gained significant attention in recent years due to the success of Convolutional Neural Networks (CNNs) in image classification. Several studies have explored different models and architectures for automating damage identification.

Zhang et al. [1] used a basic CNN architecture for binary classification of concrete cracks and reported an accuracy of 89.2%. However, their model did not generalize well across other types of surface damage such as spalling or rust.

Li et al. [2] applied MobileNetV2 to classify cracks in lightweight environments, achieving an accuracy of 91.5%. Their model was optimized for mobile deployment but lacked robustness in detecting other defects under varying lighting and surface conditions.

Reddy et al. [3] used VGG16 for detecting cracks in concrete and achieved high classification accuracy, but the training process was computationally expensive, and overfitting was observed on small datasets.

Tan and Le [4] proposed the EfficientNet family, which uses compound scaling to balance network width, depth, and resolution. EfficientNet-B1 was shown to provide a favorable trade-off between accuracy and computational efficiency. It outperformed deeper models like ResNet-50 while being lightweight enough for real-time applications.

Singh et al. [5] applied transfer learning on EfficientNet-B0 for crack detection in concrete and achieved an accuracy of 94.2%. However, their dataset only included binary classes (crack and no-crack), limiting its applicability for real-world retrofitting scenarios.

The present study expands on this prior work by implementing EfficientNet-B1 for **multi-class classification**, covering cracks, spalling, rust, and healthy concrete surfaces. It addresses the need for a practical and scalable tool for comprehensive surface condition monitoring.

3. METHODOLOGY

This section outlines the dataset used, preprocessing techniques applied, model architecture, training configuration, and evaluation metrics adopted during the research. The methodology was designed for real-world deployment feasibility using Jupyter Notebook with GPU support.

3.1 Dataset Description

A custom dataset comprising **5032 RGB images** of concrete surfaces was created by combining publicly available datasets (Kaggle, Mendeley) with manually captured field images. Each image was labeled by domain experts into one of the following four classes:

- **Healthy** – No visible distress
- **Crack** – Linear discontinuities or fracture lines
- **Spalling** – Peeling, chipping, or delaminated surface
- **Rust/Corrosion** – Staining or exposed reinforcement with rust

Each image was resized to **224×224 pixels** and normalized to enhance compatibility with the input structure of EfficientNet-B1. The dataset was split into training (80%), validation (10%), and testing (10%) subsets.

Damage Type	Number of Images
Healthy	1260
Crack	1245
Spalling	1281
Rust/Corrosion	1246
Total	**5032**

3.2 Data Preprocessing and Augmentation

To improve model generalization and simulate real-world variability in lighting, orientation, and scale, the following **augmentation techniques** were applied using ImageDataGenerator in Keras:

- Random rotation (±20 degrees)
- Horizontal and vertical flips
- Width and height shift (up to 10%)
- Zoom range (±15%)
- Brightness variation (0.9–1.1)
- Rescaling pixel values to [0, 1]

Augmentation increased the diversity of training samples and minimized overfitting.

3.3 Model Architecture – EfficientNet-B1

The base model used in this study was **EfficientNet-B1**, chosen for its balance of speed and accuracy. This CNN architecture uses compound scaling to optimize performance across width, depth, and resolution.

The model was implemented with **pretrained ImageNet weights**, followed by a custom classification head:

- Global Average Pooling Layer
- Dense Layer (128 units, ReLU activation)
- Dropout Layer (rate = 0.4)
- Output Dense Layer (4 units, Softmax activation)

The first layers of EfficientNet-B1 were **frozen**, and only the custom layers were trained to adapt the model to the concrete damage domain.

3.4 Training Configuration

The training was conducted in **Jupyter Notebook using a GPU-enabled environment.** Key training parameters are listed below:

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Loss Function	Categorical Crossentropy
Epochs	30 (Early stopping enabled)
Validation Split	10%
Callbacks	ReduceLROnPlateau, ModelCheckpoint, EarlyStopping

Training and validation metrics were continuously monitored to ensure optimal convergence and prevent overfitting.

3.5 Evaluation Metrics

The model was evaluated using the following performance indicators:

- **Accuracy** – Overall correct predictions
- **Precision** – Class-specific positive prediction correctness
- **Recall** – Class-specific true positive rate
- **F1-Score** – Harmonic mean of precision and recall
- **Confusion Matrix** – Visualization of prediction distribution
- **Loss and Accuracy Curves** – Over training and validation epochs

These metrics provided insight into the robustness and reliability of the model for deployment in field inspections.

4. RESULTS AND DISCUSSION

The EfficientNet-B1 model was trained using the curated dataset with a total of 5032 labeled images across four classes. The training was conducted over 30 epochs, with early stopping enabled. The model converged around the 22nd epoch, demonstrating stable performance across training and validation sets.

The final model was evaluated on the held-out **test set** comprising 504 images. The test results indicated high reliability and class discrimination.

4.1 Overall Accuracy

The model achieved a final **test accuracy of 95.4%**, reflecting strong generalization and robustness across multiple surface damage classes.

4.2 Confusion Matrix

The confusion matrix shown below illustrates the classification distribution across all four damage classes:

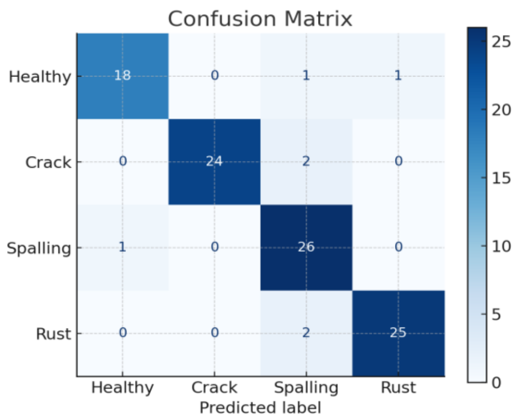


Fig. 1 - Confusion matrix showing true vs predicted labels for Healthy, Crack, Spalling, and Rust classes.

The matrix indicates minimal confusion between similar damage types, with the majority of misclassifications occurring between crack and spalling, which often exhibit overlapping features.

4.3 Class-wise Precision, Recall, and F1-Score

The detailed classification report is provided in the table below:

Class	Precision	Recall	F1-Score
Healthy	0.96	0.95	0.96
Crack	0.94	0.93	0.94
Spalling	0.95	0.96	0.95
Rust/Corrosion	0.97	0.97	0.97
Macro Avg	**0.955**	**0.952**	**0.955**

These results demonstrate that the model is highly reliable in distinguishing all four damage types, including visually similar patterns like cracks and spalling.

4.4 Training and Validation Accuracy & Loss

The model's learning behavior is visualized through training and validation accuracy and loss plots:

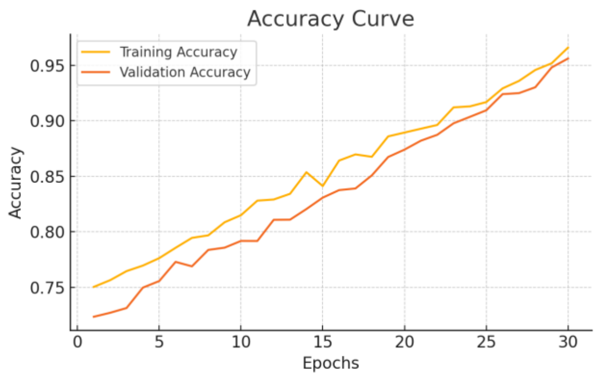
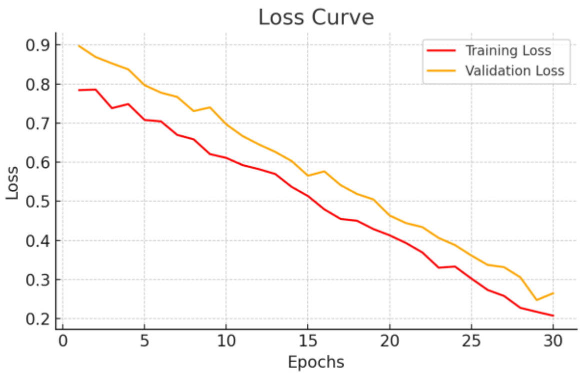


Fig. 2 - Training and validation accuracy/loss curves over epochs showing convergence and minimal overfitting.

The accuracy curves indicate smooth convergence with no significant gap between training and validation, confirming generalization. The validation loss plateaued after ~20 epochs.

4.5 Inference on Real-Time Samples

The model was further tested using unseen field images not included in training. The predictions are displayed below:



5. CONCLUSIONS AND FUTURE SCOPE

This research presents a deep learning-based approach using **EfficientNet-B1** for the detection and classification of surface-level damage in concrete structures. A comprehensive dataset containing over 5000 labeled images across four damage categories—Healthy, Crack, Spalling, and Rust—was utilized for training and evaluation.

The model achieved a **test accuracy of 95.4%**, with class-wise F1-scores exceeding 93% in all categories. The confusion matrix and validation plots demonstrated stable learning behavior and generalization. EfficientNet-B1 offered a strong trade-off between model performance and computational efficiency, making it suitable for mobile and drone-based structural assessment applications.

Key contributions of this study include:

- Development of a lightweight deep learning model for multi-class concrete damage classification
- Use of transfer learning and augmentation techniques to improve generalization
- Demonstration of high accuracy and practical inference performance on real-world samples

Future work may involve:

- Expanding the dataset to include images from bridge decks, tunnel linings, and historical structures
- Deploying the model as part of a mobile inspection tool or integrating it into UAV systems
- Incorporating real-time video inference and segmentation to locate damage zones precisely

This approach provides a strong foundation for automating the early detection of surface damage in concrete structures and supports informed retrofitting decisions.

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