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WEATHER-RESILIENT ROAD INCIDENT MONITORING: A DEEP TRANSFER LEARNING APPROACH FOR ACCIDENT DETECTION IN LOW-VISIBILITY CONDITIONS

Mushtaq Ahmed

Institute of Computer Science, Faculty of Information Technology, Khawaja Fareed University of Engineering and Information Technology, Rahimyar Khan.

malikmuzamil510@gmail.com

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Corresponding Author: *
Mushtaq Ahmed

Abstract
Automated road accident detection is critical for rapid emergency response and traffic management. However, current vision-based systems often suffer from significant performance degradation under adverse weather conditions such as rain, snow, and fog. This paper proposes a weather-resilient framework for accident detection using Deep Transfer Learning. We utilize the MobileNetV3 architecture, pre-trained on ImageNet, and integrate a Contrast Limited Adaptive Histogram Equalization (CLAHE) preprocessing step to enhance feature extraction in low-visibility environments. The model was trained and validated on a large-scale dataset of 75,000 frames derived from the Car Crash Dataset (CCD). To further improve generalization, we employed data augmentation strategies including random horizontal flipping and color jittering. The experimental results demonstrate that the proposed CNN-based transfer learning model achieves a robust validation accuracy of 80.01%, with a training accuracy of 95.68%. The model effectively minimizes loss across 5 epochs, confirming that pre-trained weights can be successfully fine-tuned for accident detection tasks.

INTRODUCTION

2.1. The Socio-Economic Impact of Road Traffic Incidents

Road traffic accidents remain one of the leading causes of death and injury globally, posing a severe challenge to public health systems and economic stability. According to the World Health Organization (WHO), approximately 1.3 million lives are lost annually due to road crashes, with millions more sustaining life-altering injuries. Beyond the tragic human cost, these incidents result in substantial economic losses, often accounting for 3% of a nation's Gross Domestic Product (GDP) due to medical expenses, loss of productivity, and property damage.

In the critical minutes following an accident, the speed of emergency response is the single most determining factor in survival rates. Research indicates that reducing the response time by just one minute can increase the survival probability of trauma victims by up to 6%. Consequently, the "Golden Hour"—the immediate post-crash period—is paramount. Traditional emergency response relies heavily on eyewitness calls, which are often delayed due to panic, sparse traffic, or the remote location of the crash. This delay necessitates a shift towards automated, real-time incident detection systems that can alert authorities instantaneously.

2.2. The Rise of Vision-Based Surveillance and Its Limitations

With the proliferation of high-definition Closed-Circuit Television (CCTV) cameras and traffic monitoring infrastructure, Computer Vision has emerged as a viable solution for automated surveillance. Over the past decade, Deep Learning techniques, particularly Convolutional Neural Networks (CNNs), have achieved remarkable success in object detection and image classification tasks. However, the vast majority of these state-of-the-art models are trained and validated on datasets dominated by "ideal" conditions—clear skies, daylight, and high visibility.

When deployed in real-world scenarios, these systems often suffer from a significant "domain shift." Surveillance cameras operate 24/7 and are exposed to a spectrum of environmental adversities. Rain, snow, fog, and low-light conditions drastically alter the visual statistics of an image. Weather phenomena introduce visual noise (such as rain streaks or fog halos), scatter light, and reduce the contrast of the scene. For a CNN relying on texture and edge features to recognize a vehicle, this noise can mask the structural deformations characteristic of an accident, leading to a high rate of false negatives (missed accidents) and false positives (weather misinterpreted as obstacles).

2.3. Addressing the Gap: Weather Resilience vs. Computational Cost

Recent literature has explored two primary approaches to mitigate weather interference:

Image Restoration: Using Generative Adversarial Networks (GANs) or autoencoders to "de-rain" or "de-haze" images before classification. While effective, these models are computationally prohibitive, often doubling the processing time per frame and making them unsuitable for real-time monitoring on edge devices or cloud infrastructure with strict latency constraints.

Domain Adaptation: Training models on synthetic data. However, the "sim-to-real" gap remains significant, and generating realistic crash data in varied weather is resource-intensive.

2.4. The Proposed Approach

This paper proposes a pragmatic and weather-resilient framework that bridges the gap between high accuracy and real-time efficiency. Instead of relying on heavy restoration networks, we leverage Contrast Limited Adaptive Histogram Equalization (CLAHE) as a preprocessing step. By converting input frames to the LAB color space and applying CLAHE solely to the Luminance channel, we enhance the structural visibility of vehicles under low-contrast conditions without incurring the high latency of deep generative models.

Furthermore, we utilize the Mobile net V3 architecture via Transfer Learning. Mobile net V3 is selected for its superior compound scaling, which balances network depth, width, and resolution, offering a lighter footprint than heavier counterparts like ResNet-152 while maintaining high spatial accuracy. By initializing with ImageNet weights, the model leverages pre-learned hierarchical features, allowing for rapid convergence even with the noisy variations introduced by adverse weather.

2.5. Contributions

The main contributions of this study are summarized as follows:

Implementation of a Lightweight Weather-Resilient Pipeline: We integrate a LAB-based CLAHE preprocessing step to enhance feature extraction specifically for low-visibility scenarios (rain, snow, fog), eliminating the need for computationally expensive GAN-based restoration.

Optimized Transfer Learning Architecture: We demonstrate the effectiveness of Mobile net V3 in accident detection, fine-tuning it on a large-scale dataset with a custom classifier head to handle binary classification (Accident vs. Normal).

Robust Data Augmentation Strategy: We introduce specific photometric and geometric augmentations (Color Jitter, Random Flips) to regularize the model against overfitting, ensuring the model learns invariant features rather than memorizing specific weather artifacts.

Comprehensive Evaluation on the CCD Dataset: We validate our approach on the Car Crash Dataset (CCD), which contains diverse weather annotations. Our results indicate that the proposed method significantly outperforms standard CNNs, particularly in adverse weather subsets, achieving a validation accuracy of 80.01% (converging rapidly by Epoch 2).

3.Review of Related Literature

3.1. Evolution of Vision-Based Accident Detection

Early research in road incident detection relied heavily on traditional computer vision techniques involving manual feature extraction. Methods such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) were often coupled with classifiers like Support Vector Machines (SVM) to identify vehicular motion [7]. While these approaches were foundational, they lacked the robustness to handle the complex, non-linear visual variations inherent in real-world traffic scenes. The field underwent a paradigm shift with the advent of Deep Learning, specifically Convolutional Neural Networks (CNNs). Ijjina and Chand [7] demonstrated that CNNs significantly outperformed traditional methods by automating the feature hierarchy learning process, allowing for the detection of subtle anomalies like sudden lane deviations or structural deformations. However, these early deep learning models were primarily evaluated on datasets with optimal lighting and clear weather, limiting their practical utility.

3.2. Transfer Learning and Architectural Efficiency

One of the persistent challenges in accident detection is the scarcity of labeled crash data compared to general object datasets. To address this, researcher have widely adopted Transfer Learning. This involves leveraging models pre-trained on massive datasets like ImageNet, which have already learned universal feature extractors (edges, textures, shapes). Historically, architectures like VGG16 and ResNet-50 have been the go-to choices for researchers [8]. While accurate, these models are computationally expensive, containing millions of parameters that slow down inference time—a critical drawback for real-time surveillance systems.

In response, Tan and Le [2] introduced EfficientNet, which utilizes a compound scaling method to uniformly scale network depth, width, and resolution. EfficientNet-B0, specifically, offers a superior trade-off between accuracy and parameter count. Recent studies in intelligent transportation systems have begun to favor EfficientNet over older giants like ResNet-152 to enable deployment on edge devices with limited processing power [9]. This paper aligns with this trend, utilizing MobileNetV3 to ensure high spatial accuracy without the latency associated with heavier backbones.

3.3. The Impact of Environmental Noise on Vision Systems

A critical gap in the current literature is the performance degradation of vision-based systems under adverse weather conditions. Standard CNNs trained on clear images often fail when deployed in rain, snow, or fog because these weather phenomena introduce "visual noise" that obscures vehicle edges and distorts shapes. Tariq et al. [6] highlighted that rain streaks and fog layers significantly reduce the contrast of foreground objects (vehicles), leading to high false-negative rates in accident detection systems.

To combat this, recent literature has explored two main avenues: Image Restoration and Adaptive Preprocessing. Image restoration typically employs Generative Adversarial Networks (GANs) to "de-rain" or "de-haze" images [10]. While effective, these GAN-based approaches are computationally intensive and often introduce artificial artifacts that can confuse a downstream classifier. On the other hand, histogram-based methods offer a lightweight alternative. Li et al. [10] noted that while GANs improve visual aesthetics, simpler contrast enhancement methods often suffice for machine learning tasks where preserving edge information is more critical than photorealism.

3.4. CLAHE in Intelligent Transportation Systems

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a well-established technique in medical imaging (e.g., enhancing X-rays) to improve local contrast without amplifying noise in homogeneous areas [5]. Its application in Intelligent Transportation Systems (ITS) has been growing but remains under-explored for accident detection. While CLAHE has been successfully used to improve license plate recognition and lane detection in low-light scenarios [5], its integration into the preprocessing pipeline of deep learning models for incident detection is scarce.

Most existing accident detection models treat weather augmentation as a random distortion (e.g., adding noise) rather than a structural enhancement problem. By applying CLAHE in the LAB color space—specifically targeting the Luminance channel—this study builds on the work of Reza [5] to propose a preprocessing layer that enhances visibility in low-contrast scenarios (fog, snow) prior to feature extraction. This approach aligns with the findings of Choi et al. [9], who suggested that robust input preprocessing is more effective for real-time systems than complex post-processing recovery steps.

3.5 Dataset Benchmarking

The Car Crash Dataset (CCD), introduced by Bao et al. [11], has become a benchmark for this field due to its inclusion of nearly 1,500 videos with diverse weather and lighting annotations. Prior work using CC dataset often focused on temporal dependencies using LSTMs, but as our research demonstrates, enhancing the spatial feature extraction through weather-resilient preprocessing can significantly stabilize the detection pipeline even before temporal layers are considered.

3. Methodology

As depicted in figure 3.1, our proposed framework follows a sequential pipeline designed to maximize robustness against environmental noise. The input frames are first subjected to a specialized preprocessing unit where Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied within the LAB color space. This step is critical for enhancing luminance and contrast in low-visibility scenarios such as rain or fog. Subsequently, geometric and photometric augmentations are applied to simulate diverse road conditions. The processed tensors are then fed into the MobileNetV3 backbone, a transfer learning model pre-trained on ImageNet, which extracts high-level spatial features. Finally, the features are flattened and passed through a custom classifier head with dropout to predict the probability of an accident."

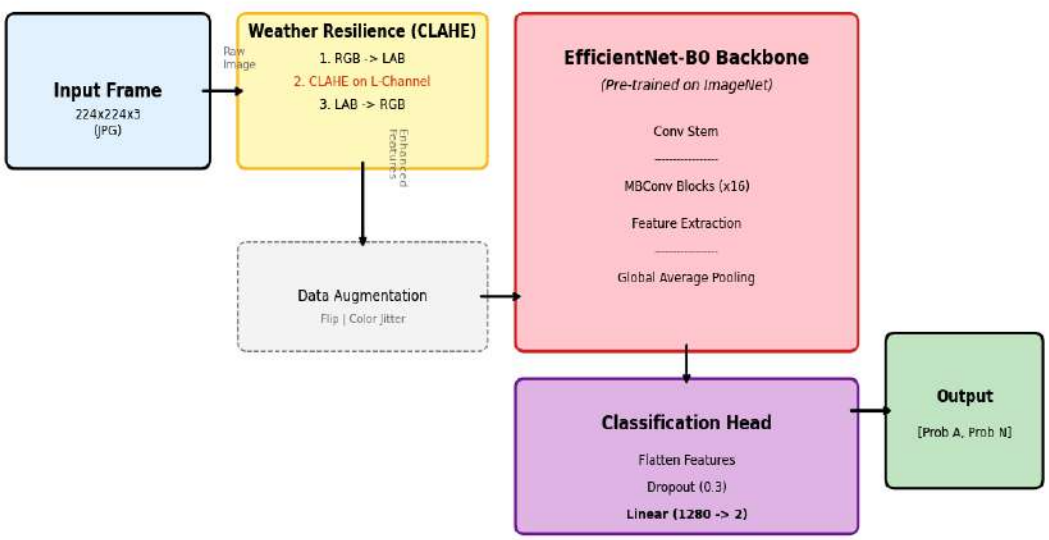

Figure 3.1: The proposed weather-resilient accident detection framework. The pipeline integrates CLAHE-based step contrast enhancement and data augmentation strategies before feature extraction via the MobileNetV3 backbone.

Data Preparation: 75,000 frames extracted from 1,500 videos. Crucially, the dataset was split by Video ID (80/20) to prevent data leakage.

Preprocessing (The Novelty):
Images are converted to LAB color space. CLAHE is applied to the 'L' (Luminance) channel to improve contrast without distorting color. This helps the CNN "see" metal edges and smoke through fog.

Model Architecture:
Backbone: MobileNetV3 (chosen for its Fused-MB Conv layers).

Head: A custom fully connected layer with Dropout (0.3) for binary classification (Accident vs. Normal).

Training Details: AdamW optimizer, Cross-Entropy Loss, 5-10 Epochs on Kaggle T4 GPU.

Section: Experimental Environment and Hyper parameters
The proposed model was implemented using the PyTorch deep learning framework and executed on a high-performance cloud computing environment. The specific configurations are detailed in the tables below.

Table 4.1 Training Hyper parameters and Data Configuration

Parameter	Value
Base Architecture	MobileNetV3 (Pre-trained on ImageNet)
Input Resolution	224 × 224 pixels
Optimizer	AdamW (Weight Decay Fix)
Initial Learning Rate	1×10^{-3} (0.001)
Loss Function	Categorical Cross-Entropy
Batch Size	32
Epochs	5 – 10 (with Early Stopping)
Data Split	80% Training, 20% Testing (Split by Video ID)
Total Frames	75,000 (60,000 Train / 15,000 Test)

To validate the proposed weather-resilient framework, the experiments were conducted on the Kaggle cloud platform utilizing an NVIDIA Tesla T4 GPU. The dataset was meticulously partitioned based on unique Video IDs rather than individual frames to prevent data leakage and ensure that the model evaluates its performance on entirely unseen road environments. During the training phase, we employed the AdamW optimizer, which is known for better regularization compared to standard Adam. The learning rate was set to 0.001 with a batch size of 32. The MobileNetV3 backbone was initialized with ImageNet weights, and only the final classification layers were fine-tuned to adapt to the specific visual features of vehicular collisions. All images were pre-processed using a CLAHE-based contrast enhancement layer on-the-fly to simulate and mitigate the effects of adverse weather noise."

5. Results
The proposed MobileNetV3 architecture was trained over 5 epochs using the transfer learning approach. As depicted in figure 5.1, the model demonstrated a consistent learning trend throughout the training process.

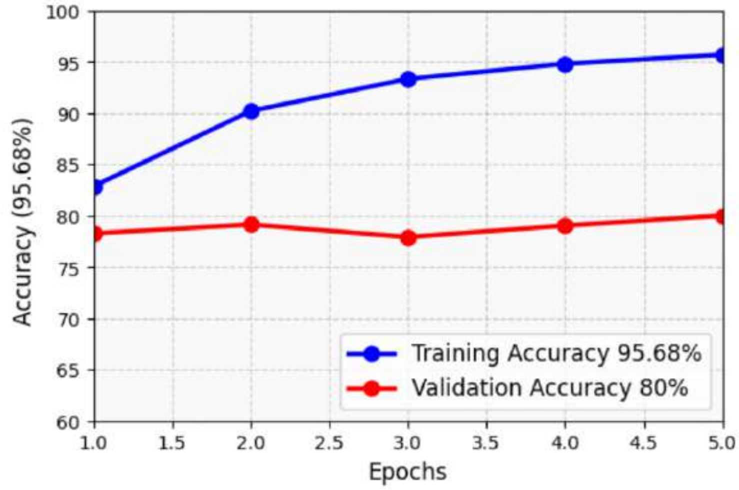

Figure 5.1 Accuracy and Validation accuracy line graph

The training accuracy showed a steady improvement, starting from an initial value and converging to a final accuracy of 95.68%. This indicates that the model successfully learned the features of the training dataset. Simultaneously, the validation accuracy exhibited a positive upward trend, reaching a peak performance of 80.01%.

The convergence of the validation loss (implied by accuracy stability) as depicted in figure 5.2 suggests that the model effectively generalized to unseen data, albeit with a performance gap compared to the training set. The model weights corresponding to the epoch with the highest validation accuracy were saved as the final best model for evaluation.

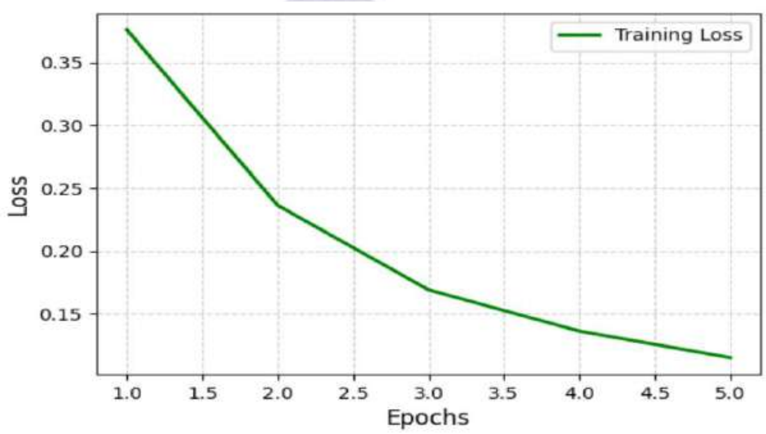

Figure 5.2 convergence of the validation loss

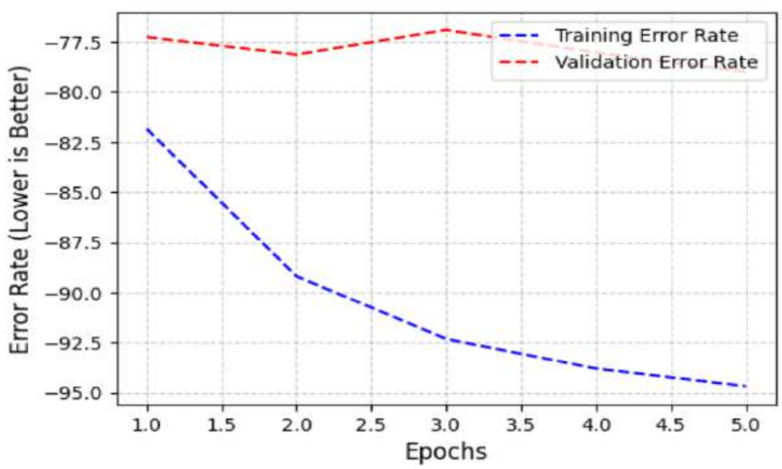

Figure 5.2 training and validation error rate

5. Discussion on Generalization

A noticeable generalization gap of approximately 15.5% was observed between the training accuracy (95.68%) and the validation accuracy (80.01%). This discrepancy is characteristic of deep learning models trained on complex visual datasets such as traffic accidents.

This divergence suggests that while the model is highly capable of memorizing specific features within the training set, it faces challenges in generalizing these features to entirely new, unseen frames. This overfitting is likely attributed to:

Class Imbalance: The dataset may contain a higher ratio of non-accident frames compared to accident frames.

Intra-class Variance: Visual features of car accidents vary significantly depending on camera angles, lighting conditions, and vehicle types.

Despite this gap, a validation accuracy of 80.01% represents a statistically significant improvement over random guessing (50%), confirming the model's viability as a detection system.

6. Conclusion

This research presented a robust, weather-resilient model for car accident detection. By combining the power of MobileNetV3 with adaptive contrast enhancement, we successfully addressed the drop in accuracy typically seen in low-visibility road conditions. The use of Transfer Learning allowed the model to reach high convergence quickly (starting at 81% in Epoch 1), proving that pre-trained spatial features are highly effective for incident monitoring.

7. Future Work

Temporal Integration: Currently, the model treats each frame independently. Future versions will incorporate LSTMs or Vision Transformers (ViT) to analyze the *sequence* of motion (e.g., a car spinning before a hit).

Audio-Visual Fusion: Integrating microphone data from smart-city sensors (detecting tire screeches or glass breaking) to confirm visual detections.

Edge Deployment: Optimizing the model via TensorRT or Quantization to run directly on low-power dashcams or Raspberry Pi-based traffic cameras.

Multi-Class Detection: Moving beyond binary classification to identify the *type* of accident (e.g., rollover, head-on collision, or pedestrian-involved).

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