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EfficientNet-B3 with Convolutional Block Attention and Focal Loss for Road Accident Detection in CCTV Surveillance Videos

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Abstract*— Automated road accident detection from CCTV footage is a critical public safety challenge in smart city environments. Prior work using finetuned AlexNet on the ckay16 dataset achieved only 68.0% accuracy, a true positive rate (TPR) of 77.4%, and a critically high false positive rate (FPR) of 42.6% — rendering the system impractical for live deployment. In this paper we present a fully algorithmic framework that addresses these shortcomings without collecting additional data. Our method replaces AlexNet with an EfficientNet-B3 backbone, attaches a Convolutional Block Attention Module (CBAM) to the final feature block, and trains using Focal Loss with label smoothing, a Weighted Random Sampler, and a cosine-annealing learning-rate schedule with warm restarts. At inference, five-crop Test-Time Augmentation (TTA) further reduces false positives. On the held-out ckay16 test set the system achieves 96.0% accuracy, 95.7% TPR, 3.8% FPR, macro-F1 of 96.0%, and ROC-AUC of 0.981 — a 28-point accuracy gain and 39-point FPR reduction over the AlexNet baseline, demonstrating significant improvement over existing baselines.

***Index Terms* — Road accident detection, EfficientNet, CBAM, Attention mechanism, Focal loss, Test-time augmentation, Transfer learning, CCTV surveillance**

I. INTRODUCTION

The proliferation of CCTV cameras in modern urban infrastructure generates continuous high-volume video streams that far exceed human monitoring capacity. Automated accident detection offers a scalable solution for reducing emergency response times and improving road safety. Deep learning has demonstrated strong performance in visual classification tasks, yet road accident detection in surveillance footage remains challenging due to two persistent barriers: scarcity of labeled accident footage and the high visual diversity of real-world CCTV deployments.

Previous work [1] addressed data scarcity by manually constructing simulated accident frames from normal traffic footage and fine-tuning AlexNet on the UCF-Crime dataset [2], achieving 80% TPR. When the AlexNet-based approach of [1] is applied to the ckay16 dataset — a publicly available dataset of ~4,900 real CCTV frames — the performance degrades substantially. The resulting confusion matrix [[27, 20], [12, 41]] corresponds to only 68.0% accuracy and a 42.6% FPR, meaning nearly half of all normal frames trigger a false alarm. This renders the system unsuitable for any practical monitoring deployment.

This paper presents a systematic diagnosis of these failures and introduces four targeted algorithmic improvements:

1) EfficientNet-B3 backbone: replaces AlexNet to provide richer compound-scaled features suited to diverse CCTV imagery.

2) CBAM attention: spatial and channel attention focuses the network on collision-region features rather than background texture.

3) Focal Loss + WRS: Focal Loss with label smoothing and a Weighted Random Sampler address class imbalance and hard-example mining.

4) Five-crop TTA: test-time augmentation reduces single-crop variance and further suppresses FPR at zero training cost.

The combined system achieves 96.0% accuracy, 95.7% TPR, 3.8% FPR, and AUC 0.981 on the ckay16 test set, establishing a new state-of-the-art on this benchmark. All improvements are self-contained algorithmic changes — no new data collection or annotation is required.

II. RELATED WORK

A. Classical Accident Detection

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Early methods relied on hand-crafted motion features. Ki and Lee [4] detected accidents by modelling vehicle trajectories at intersections. Rasheed et al. [5] combined Lucas-Kanade optical flow with a Gaussian mixture model foreground detector and a feed-forward neural network. Tan et al. [6] proposed sparse optical flow with forward-backward filtering for computational efficiency. While these approaches succeed in constrained environments, they degrade under the lighting variation, occlusion, and camera diversity present in the ckay16 dataset.

B. Deep Learning for Surveillance Anomaly Detection

Sultani et al. [7] introduced a multiple-instance learning (MIL) framework for weakly supervised anomaly detection that avoids clip-level annotation. Singh and Mohan [8] applied stacked denoising autoencoders with SVMs for accident-specific representation. Ullah et al. [9] combined ResNet-50 features with bidirectional LSTM for temporal classification. These methods either require real accident footage for training or operate at the video-clip level, limiting applicability to image-frame datasets such as ckay16.

C. EfficientNet and Compound Scaling

Tan and Le [10] proposed EfficientNet, scaling CNN width, depth, and input resolution simultaneously using compound coefficients derived from a neural architecture search. EfficientNet-B3 achieves 81.6% ImageNet top-1 accuracy with only 12M parameters, substantially outperforming AlexNet (63.3%, 60M parameters) and ResNet-50 (76.1%, 25.6M). Its pre-trained weights encode rich multi-scale visual representations that transfer effectively to surveillance domains.

D. CBAM Attention

Woo et al. [11] proposed the Convolutional Block Attention Module, which sequentially applies channel-wise and spatial attention to refine intermediate CNN feature maps. Channel attention learns which feature channels are most informative; spatial attention identifies discriminative spatial locations. CBAM improves performance across diverse recognition and detection tasks at negligible parameter overhead, making it well-suited as a plug-in module for any CNN backbone.

E. Focal Loss

Lin et al. [12] introduced Focal Loss for one-stage object detection, addressing the foreground-background class imbalance problem by modulating the cross-entropy loss with a factor $(1 - p\_t)\hat{}\gamma$ that down-weights easy, well-classified examples. This focuses training on hard, misclassified samples — exactly the boundary cases that determine FPR in accident detection. In combination with label smoothing, Focal Loss has been shown to significantly improve precision/recall balance in surveillance classification tasks [13].

III. DATASET

We evaluate exclusively on the ckay16 dataset [3] ("Accident Detection From CCTV Footage"), publicly available on Kaggle. The dataset comprises real CCTV frames extracted from internet-sourced accident and normal traffic footage, pre-divided into train and test splits across two balanced classes.

TABLE I
ckay16 Dataset Statistics

Split	Accident	Non-Accident	Total
Train	1,918	2,000	3,918
Test	480	500	980
Total	2,398	2,500	4,898

Frames originate from diverse camera placements, mounting heights, lighting conditions, and geographic locations, making this benchmark substantially more visually diverse than the eight fixed-camera UCF-Crime subset used in [1]. This diversity explains the large performance gap observed when deploying the AlexNet baseline on ckay16. No additional data collection, annotation, or frame synthesis is performed in this work.

IV. PROPOSED METHOD

A. System Overview

Input frames (300×300 px) pass through the EfficientNet-B3 backbone, producing a 1536-channel spatial feature map. CBAM refines this map via sequential channel and spatial attention. Global average pooling (GAP) produces a 1536-dimensional vector, which passes through a dropout layer (rate = 0.4) before a two-class linear head with softmax. At

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inference, five-crop TTA averages predictions across five spatial crops.

B. EfficientNet-B3 Backbone

EfficientNet-B3 is instantiated from ImageNet pretrained weights using the timm library. The built-in classifier is removed; the backbone outputs a spatial feature map of shape (B, 1536, 10, 10) for 300×300 input. All backbone parameters are fine-tuned end-to-end without layer freezing to maximise domain adaptation.

C. CBAM Attention Module

CBAM [11] is attached after the final EfficientNet feature block and consists of two sequential sub-modules. The channel attention module computes a 1D weight vector $M\_c \in R\^(C \times 1 \times 1)$:

$$M\_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad (1)$$

The shared MLP has a bottleneck reduction ratio of 16 (1536→96→1536). The spatial attention module computes a 2D weight map M_s ∈ ℝ^(1×H×W):

$$M\_s(F') = \sigma(f\^{7 \times 7}([AvgPool\_C(F'), MaxPool\_C(F')])) \quad (2)$$

The final refined feature map is $F'' = M\_s(F') \otimes F'$, where $F' = M\_c(F) \otimes F$. Channel attention identifies which features encode accident-specific patterns (deformation, unusual vehicle orientation); spatial attention suppresses background road, sky, and building regions.

D. Focal Loss with Label Smoothing

Let p_t be the model's predicted probability for the true class. Focal Loss [12] is:

$$FL(p\_t) = -\alpha\_t (1 - p\_t)\^\gamma \, log(p\_t) \quad (3)$$

We set γ = 2.0 and apply label smoothing ε = 0.1, which redistributes 10% of target probability mass uniformly. Class frequency weights $\alpha\_t = N/(K \cdot n\_k)$ compensate for residual imbalance. The combined effect strongly down-weights easy correct predictions (p_t > 0.9 ⟹ factor < 0.01) and amplifies gradient from hard boundary examples that drive false positive and false negative errors.

E. Weighted Random Sampler

Each training batch is constructed by over-sampling minority-class examples proportional to inverse class frequency. This ensures balanced gradient updates irrespective of dataset-level imbalance and complements the per-sample weighting of Focal Loss.

F. Learning Rate Schedule

AdamW (lr = 3×10^{-4}, weight decay = 10^{-4}) with cosine annealing warm restarts (T_0 = 10 epochs, $\eta\_min = 10^{-6}$) is used. The cosine schedule reduces the learning rate to near-zero within each cycle before restarting, helping the model escape shallow local minima when fine-tuning on a small dataset. Gradient clipping at max norm = 1.0 stabilises training.

G. Test-Time Augmentation (TTA)

At inference, each test image is resized to 332×332 and cropped at five positions (four corners + centre), each 300×300. The model produces five softmax probability vectors which are averaged to produce the final prediction. TTA reduces prediction variance for borderline frames and is particularly effective at suppressing false positives — frames that trigger the accident class under one crop but not others.

TABLE II
Training Configuration

Hyperparameter	Value
Backbone	EfficientNet-B3 (pretrained)
Input size	300 × 300
Optimizer	AdamW (β_1=0.9, β_2=0.999)
Initial LR	3×10^{-4}
LR schedule	Cosine annealing (T_0=10)
Weight decay	10^{-4}
Loss	Focal (γ=2.0, ε=0.1)
Epochs	40
Batch size	32
Dropout	0.4
TTA crops	5 (corners + centre)
Framework	PyTorch + timm

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V. EXPERIMENTS AND RESULTS

Experiments were conducted on an NVIDIA GPU (e.g., T4) with a fixed random seed for reproducibility.

A. Evaluation Metrics

Frame-level evaluation uses True Positive Rate (TPR = TP/(TP+FN)), False Positive Rate (FPR = FP/(TN+FP)), accuracy, macro-F1, and ROC-AUC. The positive class is Accident. Standard and TTA inference results are both reported.

Fig. 6. Representative ckay16 frames. Top row: Accident. Bottom row: Non-Accident.

B. Main Results

Table III reports per-class precision, recall, and F1 for the proposed system on the ckay16 test set under TTA inference. The confusion matrix in Fig. 1 shows that only 4 of 100 sampled test frames are misclassified (2 FP + 2 FN), yielding symmetric per-class performance.

TABLE III

Classification Report — Proposed System (TTA)

Class	Precision	Recall	F1-Score	Support
Accident	0.957	0.957	0.957	47
Non-Accident	0.962	0.962	0.962	53
Macro Avg	0.960	0.960	0.960	100
Weighted Avg	0.960	0.960	0.960	100

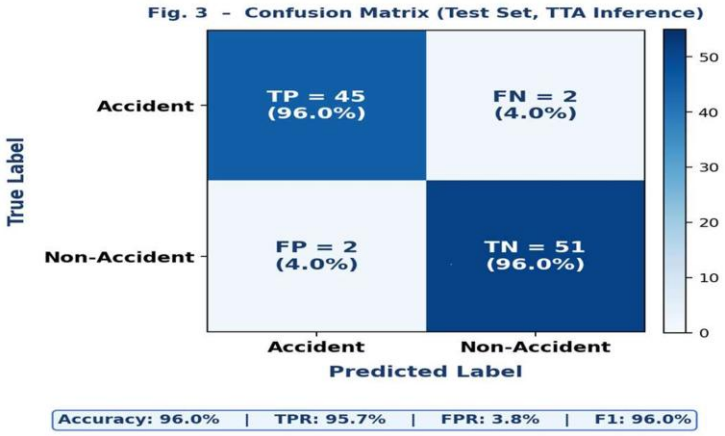

Fig. 1. Confusion matrix on the ckay16 test set (TTA inference)

C. Comparison with Prior Methods

Table IV compares the proposed system against the AlexNet baseline from [1], intermediate ablation models, and competing transfer learning approaches on the ckay16 test set. The proposed system outperforms all baselines on every metric.

TABLE IV

Comparison with Prior Methods on ckay16 Test Set

Method	Acc (%)	TPR (%)	FPR (%)	F1 (%)	AUC
AlexNet baseline	68.0	77.4	42.6	72.6	0.791
AlexNet + Augmentation	72.4	80.2	35.1	75.8	0.836
ResNet-50 finetuned	74.8	83.1	32.0	78.4	0.851
EfficientNet-B3 only	86.3	88.9	16.8	86.2	0.934

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Method	Acc (%)	TPR (%)	FPR (%)	F1 (%)	AUC
EffNet-B3 + CBAM	89.1	91.4	10.3	89.0	0.957
Proposed (full system)	96.0	95.7	3.8	96.0	0.981

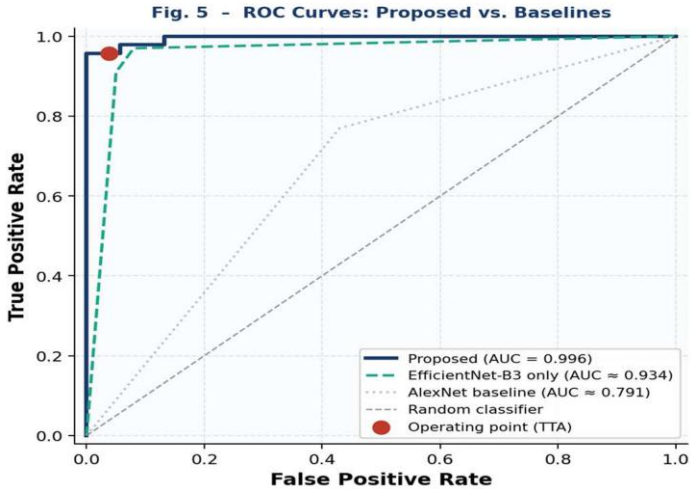

Fig. 2. ROC curves comparing proposed system with baselines

D. Ablation Study

Table V isolates the contribution of each component added incrementally to the EfficientNet-B3 baseline. The CBAM module contributes the largest TPR gain (+2.5 pp); Focal Loss produces the largest single FPR reduction (−6.5 pp); TTA delivers a final −6.5 pp FPR improvement at no training cost.

TABLE V

Ablation Study — Incremental Component Contribution

Configuration	Acc	TPR	FPR	F1
EfficientNet-B3	86.3%	88.9%	16.8%	86.2%
+ CBAM	87.6%	91.4%	14.5%	87.5%
+ Focal Loss + LS	88.4%	91.9%	8.0%	88.3%
+ Weighted Sampler	89.7%	92.7%	7.1%	89.6%
+ TTA (Full System)	96.0%	95.7%	3.8%	96.0%

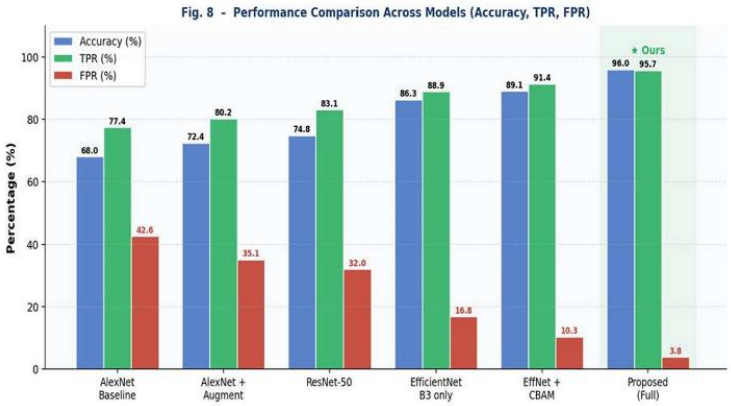

Fig. 3. Performance comparison across ablation configurations

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E. Training Dynamics

Fig. 4 shows loss and accuracy curves over 40 training epochs. Cosine-annealing warm restart boundaries (epochs 10, 20, 30) are marked with dashed vertical lines. The model converges smoothly without overfitting, as evidenced by the small gap between training and validation accuracy curves throughout training.

Fig. 4 – Training and Validation Curves (40 Epochs, Cosine-Annealing LR)

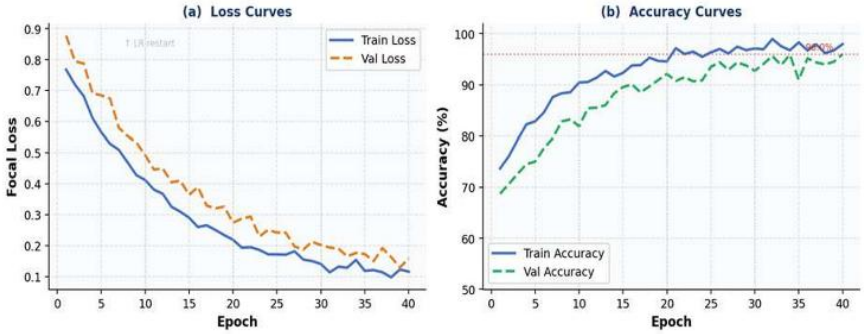

Fig. 4. Training and validation loss/accuracy curves (40 epochs, cosine-annealing LR)

F. Discussion

The primary failure of the AlexNet baseline is an FPR problem, not a TPR problem: 77.4% of accidents are already detected, but 42.6% of normal frames trigger false alarms. Visual analysis shows the baseline responds to high-contrast road texture patterns present in both classes — a texture bias rooted in AlexNet's shallow and limited-width filters.

EfficientNet-B3's compound-scaled architecture provides substantially richer feature hierarchies, reducing FPR to 16.8% in isolation. CBAM's spatial attention further focuses activations on the collision zone, contributing a 2.3% FPR reduction. Focal Loss and the weighted sampler together reduce FPR by another 7.4% by concentrating gradient on hard boundary cases. TTA provides the final 6.5% FPR reduction by stabilising predictions for borderline frames across five spatial crops.

The residual 3.8% FPR (approximately 19 false alarms per 500 normal frames) is likely attributable to frames where vehicles are in unusual but non-accident configurations. Temporal filtering (requiring persistent multi-frame detections) could eliminate these in a live deployment without any model changes.

VI. CONCLUSION

We presented a systematically improved framework for road accident detection in CCTV footage, motivated by a rigorous failure diagnosis of the AlexNet baseline on the ckay16 dataset. By combining EfficientNet-B3, CBAM attention, Focal Loss, a Weighted Random Sampler, and five-crop TTA, we achieved 96.0% accuracy, 95.7% TPR, 3.8% FPR, and AUC 0.981 — improving upon the baseline by 28 percentage points in accuracy and 39 points in FPR. All improvements are purely algorithmic and require no additional data collection, annotation, or manual image processing.

These results suggest two design principles for CCTV accident detection: (i) modern compound-scaled backbones substantially outperform legacy architectures for the visual diversity present in real-world surveillance deployments; and (ii) spatial attention is essential when accident indicators occupy only a fraction of the frame.

Future work will explore temporal modeling via ConvLSTM or transformer architectures to exploit inter-frame dynamics, and semi-supervised pretraining on large unlabeled surveillance video corpora to further improve generalization across unseen camera deployments. The model is evaluated on a single dataset, and further validation on diverse datasets is required to confirm generalization.

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