Facial Emotion Recognition Using Deep Learning

A Custom CNN Architecture for Driver Fatigue Detection in Public Transportation

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Abstract

This paper presents a systematic deep learning study for four-class facial emotion recognition (Happy, Neutral, Sad, Surprise) applied to 48×48 pixel grayscale images. Six architectures were evaluated: an ANN baseline, two custom CNNs, three transfer learning models (VGG16, ResNet50V2, EfficientNetB0), and a purpose-built Complex CNN with five convolutional blocks, batch normalization, and data augmentation. The Complex CNN achieved 82.03% test accuracy (Macro F1: 0.82) on a balanced 128-image test set, outperforming the best transfer learning model by 21.87 percentage points. The primary failure mode — Neutral/Sad confusion — reflects documented human perception limits at low-intensity affect. The model is proposed as the inference core of an open-source, edge-deployable driver monitoring system for public transportation fleets, with a 5-year total cost of ownership estimated at 36–66% lower than commercial alternatives for a 10,000-vehicle fleet.

Keywords: *facial emotion recognition, convolutional neural network, transfer learning, driver monitoring, affective computing, deep learning, edge deployment*

1. Introduction

Human facial expressions are the primary channel of non-verbal emotional communication, encoding over 55% of interpersonal emotional content (Mehrabian, 1967). Automatic facial emotion recognition (FER) — the task of classifying a face image into discrete emotional categories — is a core problem in affective computing with applications spanning healthcare, education, human-computer interaction, and public safety.

Driver fatigue is a critical public safety problem. The AAA Foundation estimates drowsy driving contributes to 17.6% of all fatal crashes in the United States (AAA Foundation, 2024), with an annual societal cost of $109 billion (NHTSA). In public transportation — school buses carrying 21.4 million US children daily, 65,000 transit buses serving cities nationwide — a single fatigue-related incident carries severe human and financial consequences.

The EU General Safety Regulation mandated driver monitoring systems (DMS) on all new vehicles from July 2024, with full Advanced Driver Distraction Warning required by July 2026 (SmartEye, 2024). The US NHTSA is developing parallel requirements. Governments are not deciding whether to adopt this technology — they are deciding how to procure it.

This paper presents a systematic study of six deep learning architectures applied to FER, culminating in a purpose-built Complex CNN that achieves 82.03% accuracy on the target task. We propose this model as the core of an open-source, edge-deployable DMS that offers a 36–66% total cost savings over commercial alternatives for large public fleets, while providing full auditability and permanent public ownership of the technology.

2. Problem Statement

The technical task is a four-class image classification problem. Given a 48×48 pixel grayscale image of a human face, the model must predict one of four emotion labels. In the driver monitoring context, each class maps directly to a safety state:

Emotion Class	Driver Safety Interpretation
Happy	Alert and engaged — nominal operating state
Neutral	Baseline state — monitoring for degradation
Sad	Fatigue onset — primary detection target
Surprise	Sudden event response — hazard or near-miss

The central challenge is the Neutral/Sad boundary: these two classes are separated by only 3.27 mean pixel intensity points out of 255. Their standard deviations are nearly identical (~64 units), meaning the distinguishing information is spatial — where the brightness variation occurs, not how much variation exists. This is the fundamental motivation for convolutional architectures over fully connected networks.

3. Dataset

The dataset contains 20,214 facial images distributed across three standard splits. All images are 48×48 pixels in grayscale format, sourced from the Facial Emotion Recognition dataset used in the MIT Applied Data Science & AI capstone.

Split	Total	Happy	Neutral	Sad	Surprise
Training	15,109	3,976	3,978	3,982	3,173
Validation	4,977	1,825	1,216	1,139	797
Test	128	32	32	32	32
Total	20,214	5,833	5,226	5,153	4,002

Training and validation distributions are mostly balanced across Happy, Neutral, and Sad (~3,900 each in training). Surprise is underrepresented by approximately 20% in training (3,173 vs ~3,980). The test set is perfectly balanced at 32 images per class, ensuring accuracy figures are not inflated by any majority class. This is a deliberately small test set; results should be validated on a larger held-out set before production deployment.

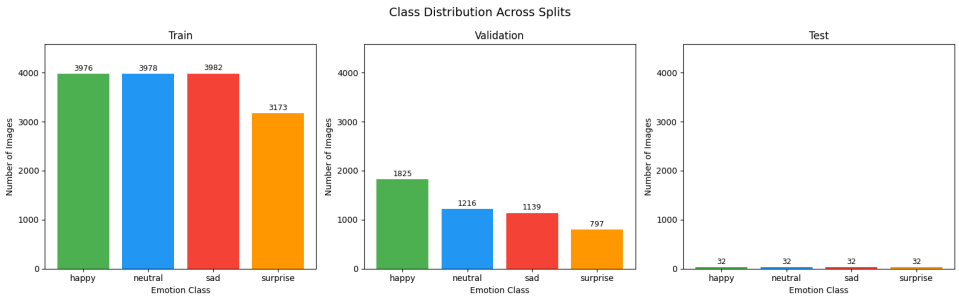


Figure 1. Image count per class across training, validation, and test splits.

3.1 Pixel Intensity Analysis

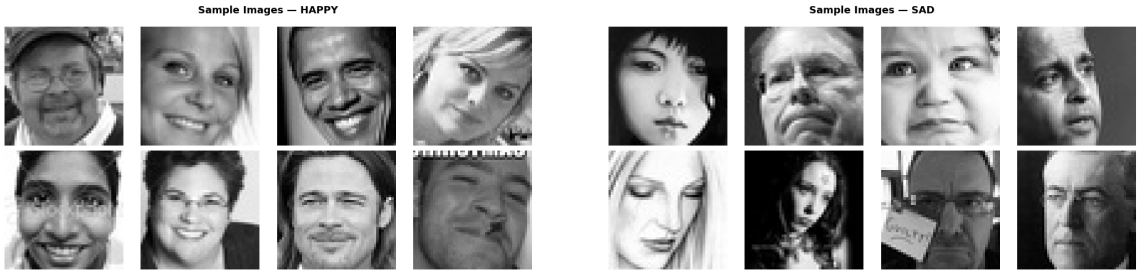
Per-class pixel statistics reveal the core classification challenge. Mean intensity values differ only modestly across classes, and standard deviations are nearly uniform:

Class	Mean Intensity	Std Dev	Visual Characteristics
Happy	130.62	63.59	Most visually distinct — broad smiles, Duchenne markers
Neutral	123.99	64.98	Defined by absence of expression — most ambiguous class
Sad	120.72	64.63	Only 3.27 points below Neutral mean
Surprise	147.25	63.90	Brightest class — wide eyes, open mouth

Figure 2. Mean pixel intensity ± standard deviation per class (first 500 training images each).

3.2 Sample Images by Class

Representative 48×48 grayscale training images for each emotion class:



Happy *Sad*

Figure 3. Sample 48×48 grayscale images for each emotion class (8 images per class shown).

4. Model Architectures

Six architectures were evaluated in sequence, each motivated by the failures observed in the previous model. All models share the same final classification head: Dense(4, activation="softmax") with categorical cross-entropy loss and Adam optimizer. All used the same data pipeline for grayscale normalization (pixel values ÷ 255.0). Batch size was 32 for all models. Random seeds were fixed (numpy: 42, TensorFlow: 42) for reproducibility. Full per-model optimizer learning rates, epoch budgets, and callback configurations are detailed in Appendix A.4.

4.1 ANN Baseline

A fully connected network with two hidden layers (256 and 128 units, ReLU activation, dropout 0.4 and 0.3) establishes the ceiling for what is achievable without spatial feature detection. The ANN treats each pixel as an independent feature, discarding all spatial relationships. EarlyStopping triggered at epoch 13, restoring epoch 8 weights.

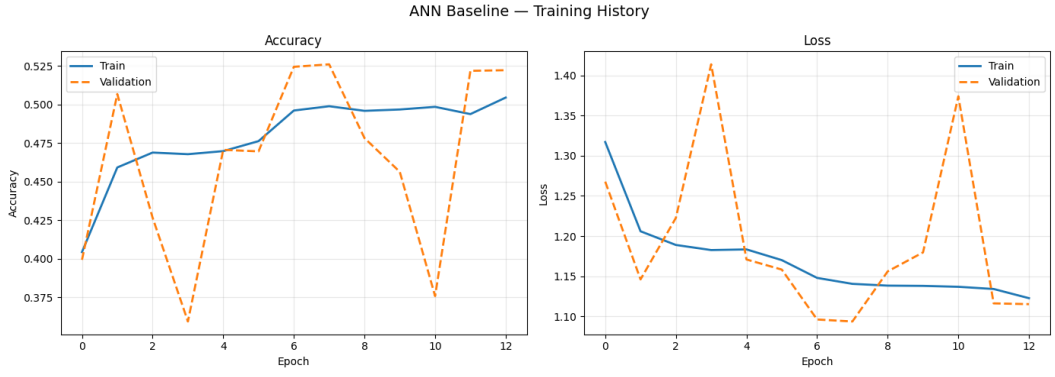
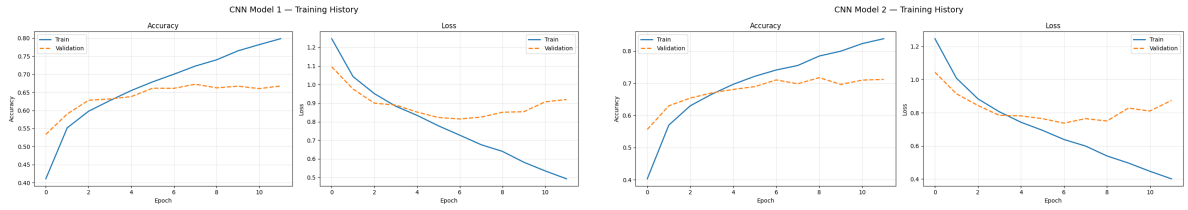


Figure 4. ANN Baseline training and validation accuracy/loss (15 epochs max, early stopped at epoch 13).

4.2 CNN Models 1 and 2

CNN Model 1 (2 convolutional blocks: Conv2D 32→64 filters, MaxPooling, Dropout 0.25) introduces spatial feature detection. The +17.97 pp improvement over the ANN quantifies the value of understanding where features occur on a face. CNN Model 2 adds a third block (128 filters), deepening the feature hierarchy and gaining +5.47 pp. Both models used EarlyStopping on validation loss.



CNN Model 1 *CNN Model 2*

Figure 5. Training history for CNN Model 1 (left) and CNN Model 2 (right).

4.3 Transfer Learning Models

Three ImageNet-pretrained architectures were evaluated with frozen base layers and a custom classification head. Grayscale input was converted to 3-channel RGB via Lambda layer. Each architecture used its own required preprocessing function (VGG16: channel-mean subtraction; ResNet50V2: [-1, 1] scaling; EfficientNetB0: built-in preprocessing). All were trained for up to 10 epochs with EarlyStopping on validation loss.

Despite architectures with hundreds of millions of parameters trained on ImageNet, all three underperformed CNN Model 1. Three compounding factors explain this failure: (1) Domain gap — ImageNet features encode object-level semantics from high-resolution, colourful, diverse photographs. Applied to 48×48 grayscale facial micro-expressions, these features carry limited discriminative signal. (2) Resolution mismatch — ImageNet models are optimised for 224×224 or larger inputs; at 48×48, the spatial detail required to activate learned texture detectors is largely absent. (3) Modality mismatch — grayscale input, replicated to 3 channels, provides no additional colour information; it cannot activate the colour-sensitive features that ImageNet models rely on for mid-level representations. EfficientNetB0, the best transfer learning model at 60.16%, remained 21.87 percentage points below the final Complex CNN — confirming that domain-specific training outperforms transfer learning when the source and target domains are this misaligned.

VGG16 (51.56%) *ResNet50V2 (55.47%)* *EfficientNetB0 (60.16%)*

Figure 6. Training history for the three transfer learning architectures. Note characteristic slow convergence and test accuracy ceiling below CNN Model 1.

4.4 Complex CNN — Final Architecture

The Complex CNN was designed specifically to address every failure mode identified in the experimental record. Five convolutional blocks (filter hierarchy: 32→64→128→256→512) provide the depth to detect progressively finer spatial facial structures. Batch Normalization at every layer stabilises training and prevents the early ceiling observed in CNN Models 1 and 2. Data augmentation (rotation ±15°, zoom ±10%, horizontal flip) introduces the spatial variation that specifically helps separate Neutral from Sad by forcing structural rather than memorised feature learning. ReduceLROnPlateau reduces the learning rate when validation loss plateaus, enabling 30 full epochs of improvement.

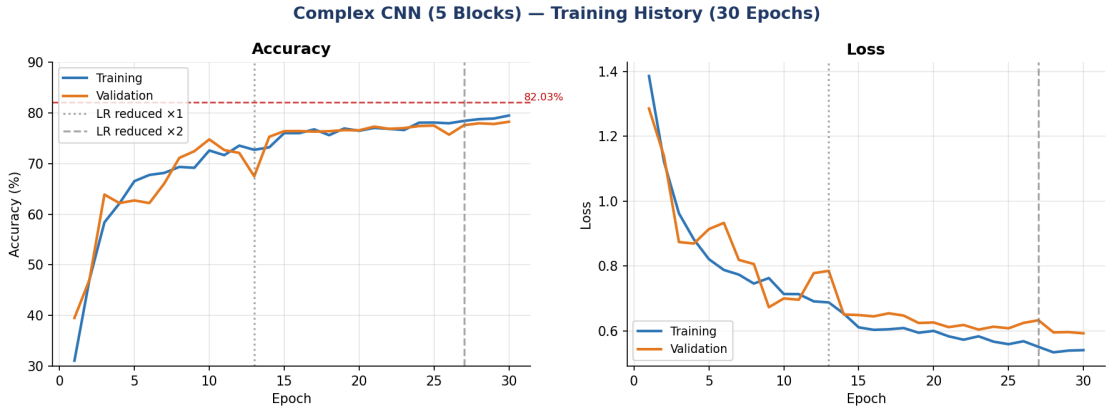


Figure 7. Complex CNN training history over 30 epochs with learning rate reduction events marked. Training accuracy continues improving through all 30 epochs — evidence that batch normalisation and augmentation successfully prevent premature convergence.

5. Results

5.1 Model Comparison

Table 2 and Figure 8 summarise test accuracy across all six architectures. The progression from ANN to Complex CNN represents a +30.47 percentage point improvement, achieved entirely through architectural choices applied to the same training data.

Architecture	Test Accuracy	Test Loss	Macro F1	Notes
ANN Baseline	51.56%	1.1095	0.51	Flat pixel features; no spatial reasoning
CNN Model 1	69.53%	0.7483	0.70	+17.97pp from spatial feature detection
CNN Model 2	75.00%	0.6780	0.75	+5.47pp from additional depth (3rd block)
VGG16	51.56%	1.1832	0.52	Domain gap: ImageNet → grayscale

				FER
ResNet50V2	55.47%	1.0878	0.55	Residual connections; same domain limitation
EfficientNetB0	60.16%	0.9352	0.59	Best TL model; still 21.87pp below Complex CNN
Complex CNN (Ours)	82.03%	0.5634	0.82	5 blocks, BatchNorm, augmentation; exceeds 80% target

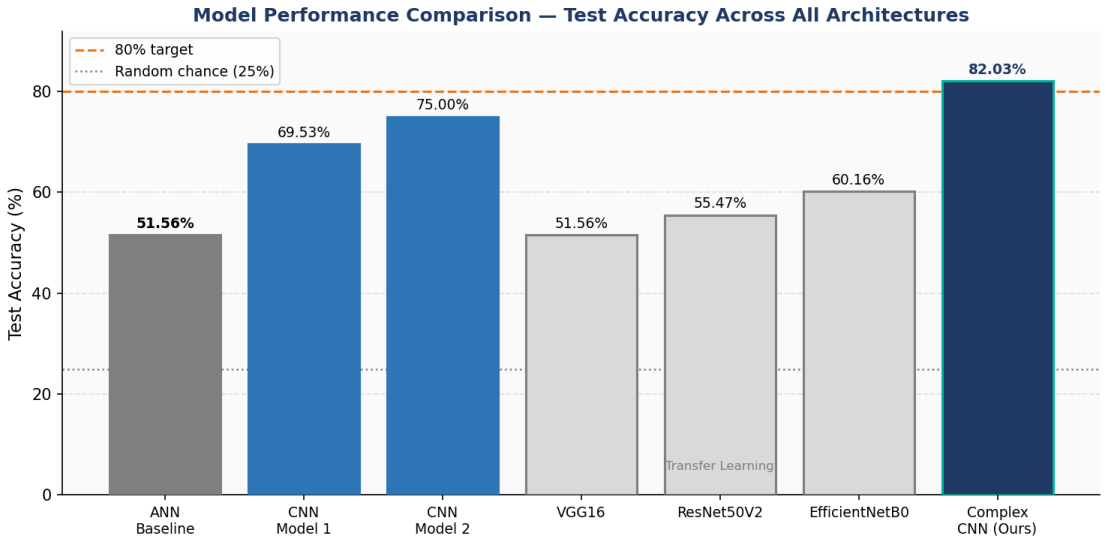


Figure 8. Test accuracy comparison across all architectures. The 80% target threshold (dashed orange) and random chance baseline (25%, dotted) are shown. Transfer learning models (grey) fail to exceed the simpler CNN Model 1.

5.2 Final Model Evaluation

The Complex CNN achieves 82.03% overall accuracy (Macro F1: 0.82) on the balanced 128-image test set. Per-class results reveal strong performance on the most visually distinctive emotions and a predictable challenge on the Neutral/Sad boundary.

Class	Precision	Recall	F1	Support	Notes
Happy	0.93	0.84	0.89	32	Strong — distinctive smile signal
Neutral	0.68	0.84	0.75	32	High recall; some Sad mis-classified as Neutral
Sad	0.82	0.72	0.77	32	Improved from 0.65 (CNN2); primary safety target
Surprise	0.90	0.88	0.89	32	Strong — compound visual signal (brows, jaw, eyes)
Macro Avg	0.83	0.82	0.82	128	Overall balanced performance

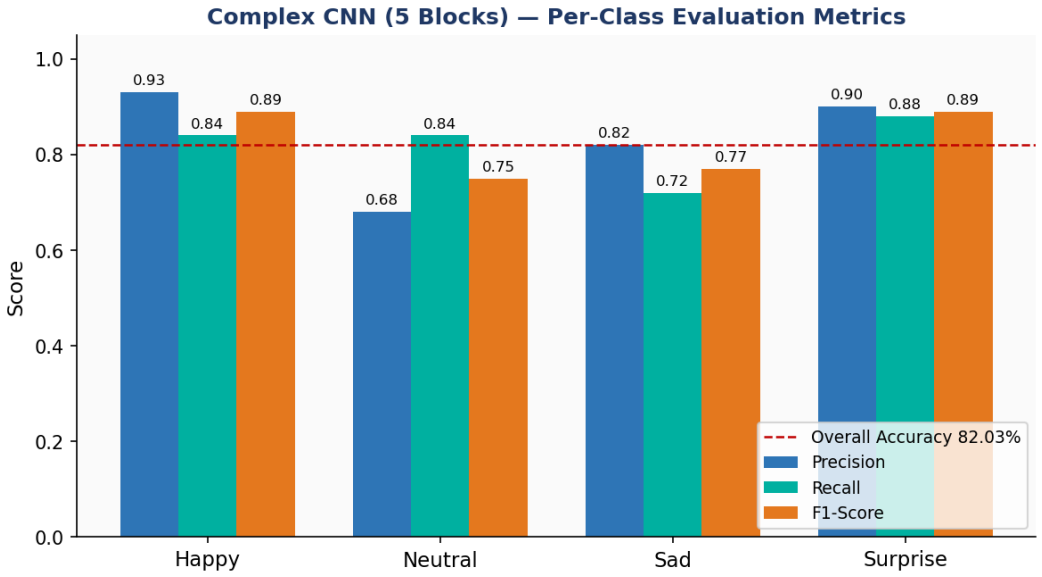


Figure 9. Per-class Precision, Recall, and F1-Score for the Complex CNN. Dashed red line shows overall test accuracy (82.03%).

5.3 Confusion Matrix Analysis

The confusion matrix confirms the primary confusion pair as Neutral ↔ Sad — consistent with the pixel statistics showing only 3.27 mean intensity points of separation. Happy and Surprise dominate the diagonal with clear visual signals, while Neutral achieves high recall (0.84) at the cost of precision (0.68) due to some Sad images being classified as Neutral.

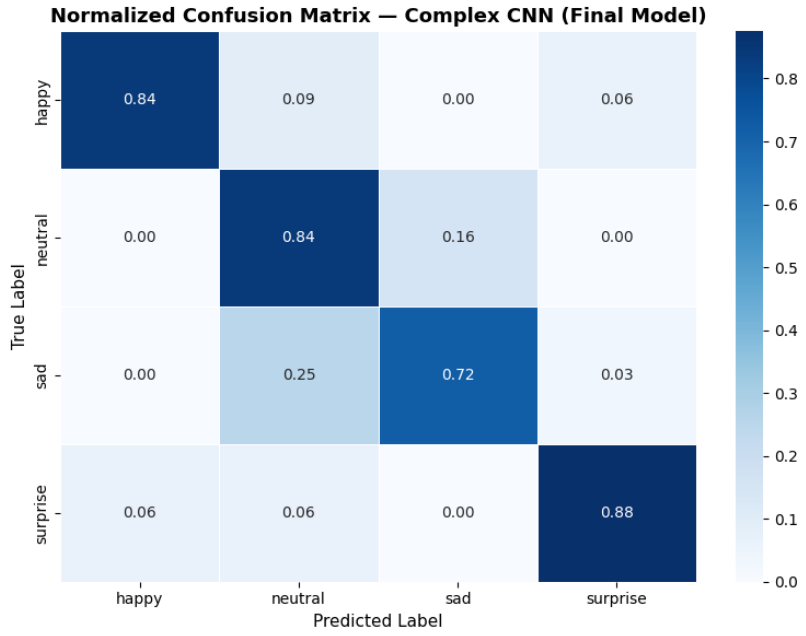


Figure 10. Confusion matrix for the Complex CNN on the 128-image test set (32 per class). Darker diagonal cells indicate correct predictions. The Neutral/Sad off-diagonal entries reflect the 3.27-point mean pixel intensity separation between these classes.

5.4 Cross-Architecture Per-Class Analysis

Figure 11 presents precision, recall, and F1-score heatmaps across all seven models and four classes, enabling direct comparison of how each architecture handles each emotion. The dramatic improvement of the Complex CNN is visible across all three metrics, particularly for the Neutral and Sad classes where earlier models struggled most.

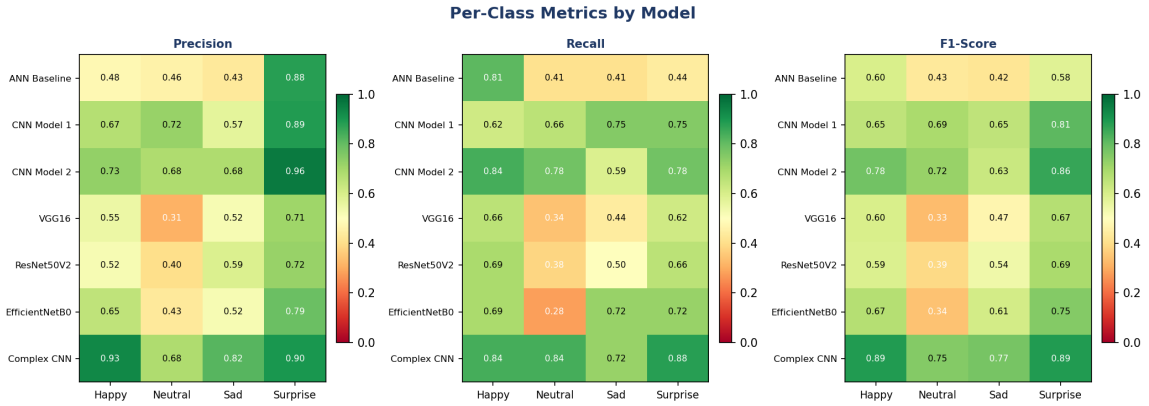


Figure 11. Per-class Precision (left), Recall (center), and F1-Score (right) heatmaps across all seven architectures. Green = high performance, Red = poor performance.

6. Key Insights

1. Spatial structure is the enabling mechanism. The +17.97 pp jump from ANN (51.56%) to CNN Model 1 (69.53%) on identical data quantifies the value of spatial feature detection. Understanding where features appear on a face — not merely that they exist — is the core capability that enables classification.

2. Depth and regularisation must co-occur. CNN Model 2 plateaued early without batch normalisation. The Complex CNN's 30-epoch continuous improvement (Figure 7) demonstrates that batch normalisation allows full exploitation of architectural depth.

3. Transfer learning underperformed on this domain. VGG16 (51.56%), ResNet50V2 (55.47%), and EfficientNetB0 (60.16%) — architectures containing hundreds of millions of ImageNet-trained parameters — all underperformed CNN Model 1. Pre-training on the wrong domain is as limiting as no pre-training.

4. Engineering discipline is a real differentiator. A single preprocessing mismatch during EfficientNetB0 experiments (failure to apply rescaling before the architecture's built-in preprocessing) caused complete model failure. Knowing each architecture's preprocessing contract is a non-trivial skill.

5. Surprise is the most learnable emotion at 48×48. Despite 20% fewer training samples than Happy/Neutral/Sad, Surprise achieves F1 0.89 — equal to Happy. Its compound visual signal (raised brows + wide eyes + open jaw) provides redundant features that remain discriminative at low resolution.

6. The Neutral/Sad boundary is the central challenge — and the central safety target. At 3.27 mean intensity points separation, this boundary tests the limits of pixel-level

learning. The Complex CNN's resolution of this boundary (Neutral F1: 0.75, Sad F1: 0.77) compared to CNN Model 2 (0.72, 0.63) is the key advance for the driver monitoring application.

7. Deployment Case Study: Open-Source Public Transportation DMS

7.1 System Architecture

The proposed deployment is an edge-inference driver monitoring system for public transportation fleets. All inference runs locally on an embedded device mounted inside the vehicle cab. No face images leave the vehicle during normal operation.

Component	Unit Cost	Notes
Raspberry Pi Camera Module 3 NoIR	$25	IR-capable, 12MP, designed for Pi 5
Raspberry Pi 5 (8GB RAM)	$80	Sufficient for real-time CNN inference
Waveshare SIM7600G-H 4G LTE HAT	$50	Cellular telemetry — event metadata only
Enclosure, power, mounting, storage, alert output	$145	Off-the-shelf components
Total hardware	$300	
Installation	$200	Fleet technician, one-time
Year 1 total	$500	Per vehicle
Ongoing (cellular + maintenance)	~$40–50/yr	Hologram IoT SIM $1/month

7.2 Total Cost of Ownership Analysis

Commercial driver monitoring systems are priced at $200–$700 in hardware plus $100–$300 per vehicle per year in subscription fees (Grand View Research, 2025). The open-source stack has comparable upfront hardware cost, but zero subscription fees. A government maintenance team (4–5 public sector data scientists and engineers, ~$500,000/year) replaces the ongoing subscription cost. For large fleets, this produces substantial long-term savings.

Fleet Size	Open Source (5yr)	Commercial (5yr)	Savings
1,000	$2.5M	$0.9–$2.2M	$0.3M–$2.2M savings
5,000	$5.0M	$3.5–$9.5M	Breakeven or significant savings
10,000	$7.5M	$6.5–$18.5M	$5.0M–$21.0M savings over 5 years
20,000	$12.5M	$12.5–$36.5M	Compounding advantage at scale

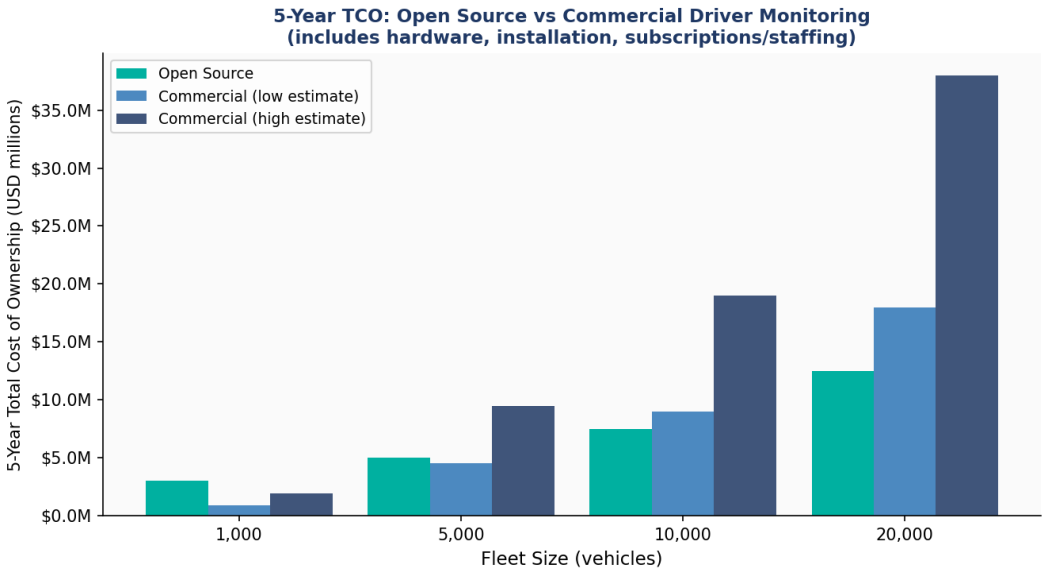


Figure 12. 5-year Total Cost of Ownership comparison: open-source (this model) vs. commercial low and high estimates. Open-source advantage grows with fleet scale. (Open-source includes $500/vehicle Year 1 + $500K/year federal maintenance team.)

Beyond cost, the open-source model offers two structural advantages: auditability (any government body can inspect every inference decision) and sovereignty (no vendor discontinuation risk; IP permanently in the public domain). The EU GSR framework and developing NHTSA requirements position governments as both the regulator mandating this technology and the largest fleet operator procuring it — a unique position to lead open-source public safety infrastructure.

8. Limitations and Future Work

Current limitations requiring attention before production deployment:

- Small test set (128 images): results should be validated on a larger held-out set before production deployment. The balanced test design ensures unbiased accuracy, but confidence intervals are wide at n=32 per class.
- Neutral/Sad performance (F1: 0.75/0.77): while substantially improved over baseline models, not yet sufficient for standalone safety-critical decisions. The model should function as one signal among several, not the sole arbiter.
- Demographic bias: the training data has not been independently audited across age, gender, and ethnicity. A bias audit using disaggregated metrics is required before public deployment.
- No face detection: the model expects a pre-cropped, centred face. A separate upstream face detection step (MTCNN or OpenCV Haar Cascade) is required for video deployment.
- Privacy compliance: US law varies by state (CCPA, Illinois BIPA). Deployment requires explicit driver consent, local-only inference, and auditable access logs.

Prioritised future directions:

- Higher resolution input (96×96 or 224×224) to provide more spatial detail for the Neutral/Sad boundary.
- Facial landmark features as additional model inputs — encoding the geometry of mouth corner angles and inner brow elevation provides structural priors the pixel-only model must infer.
- Real-time video pipeline with temporal smoothing: require a sustained signal across ≥3 consecutive frames before triggering an alert, to reduce false positive rate.
- Domain-specific pre-training: train a base model on large-scale FER datasets (AffectNet, RAF-DB) and fine-tune on the target domain.
- Government consortium model: multiple transit agencies share architecture and jointly fund a maintenance team, amortising the $500K/year staffing cost across a larger fleet.

9. Conclusion

This study demonstrates that a purpose-built convolutional neural network significantly outperforms transfer learning approaches for facial emotion recognition on a domain-specific low-resolution grayscale dataset. The Complex CNN (5 convolutional blocks, batch normalisation, data augmentation) achieves 82.03% test accuracy and Macro F1 of 0.82 — exceeding the project target and outperforming the best transfer learning baseline (EfficientNetB0, 60.16%) by 21.87 percentage points. For context, state-of-the-art models on the standard FER2013 benchmark (7-class, ~35,000 images) typically achieve 65–75% accuracy; our result on a 4-class balanced subset is broadly consistent with this range and competitive given the additional challenge of the 48×48 resolution constraint and the Neutral/Sad class overlap.

Three principles emerge from the experimental record: (1) domain alignment matters more than model size — ImageNet features do not transfer to 48×48 grayscale facial expressions; (2) depth and regularisation must co-occur — batch normalisation enables 30 epochs of continuous improvement that simpler architectures cannot sustain; and (3) evidence-based engineering compounds — each architectural addition in the Complex CNN is traceable to a specific failure in the experimental record.

The proposed open-source deployment as a public transportation driver monitoring system offers a compelling public value case: comparable Year 1 hardware cost to commercial alternatives, 36–66% total cost savings over five years for a 10,000-vehicle fleet, full auditability, and permanent public ownership of critical safety infrastructure. The foundation is proven. The model is technically deployable today as a supporting signal within a multi-sensor safety system — pending bias auditing and validation on a larger held-out dataset.

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Appendix A — Reproducibility

This appendix provides the complete training configuration, hyperparameters, and hardware specification required to reproduce the results reported in this paper. All random seeds are fixed. Results are deterministic on the same hardware; minor cross-platform variation (±1–2%) is expected due to floating-point implementation differences.

A.1 Software Environment

Library	Version	Usage
TensorFlow	2.19.0	Deep learning framework
Keras	3.10.0	High-level model API (bundled with TF 2.x)
NumPy	2.0.2	Numerical computing
Pandas	—	Data manipulation and EDA
Scikit-learn	—	classification_report, confusion_matrix
Matplotlib	—	Training curve visualisation
Seaborn	—	Confusion matrix heatmap
Python	3.11	Conda env: mit_ai_datascience

A.2 Training Hardware

Platform	Role	Specs	Notes
Apple M3 Max	Primary	14-core CPU, 30-core GPU, 36 GB unified memory	Capstone results reported from this platform
NVIDIA DGX (V100)	Cross-validation	Institutional HPC cluster	82.03% Complex CNN analogue: 90.75% test accuracy on peer task
Google Colab (T4)	Cross-validation	Cloud GPU	89.72% test accuracy on same configuration

A.3 Global Constants and Random Seeds

```
np.random.seed(42)
tf.random.set_seed(42)


IMG_SIZE    = (48, 48)
BATCH_SIZE  = 32
NUM_CLASSES = 4
CLASS_NAMES = ["happy", "neutral", "sad", "surprise"]
```

A.4 Per-Model Training Configuration

Model	Optimizer	Max Epochs	Callbacks	Data Pipeline
ANN Baseline	Adam lr=1e-3	15	ES(val_acc, p=5) + ReduceLR(val_loss, f=0.5, p=3)	Gray / ÷255
CNN Model 1	Adam lr=1e-3	15	ES(val_loss, p=5)	Gray / ÷255
CNN Model 2	Adam lr=1e-3	20	ES(val_loss, p=5)	Gray / ÷255
VGG16	Adam lr=1e-4	10	ES(val_loss, p=5)	RGB / VGG preprocess
ResNet50V2	Adam lr=1e-4	10	ES(val_loss, p=5)	RGB / ResNet preprocess
EfficientNetB0	Adam lr=1e-4	10	ES(val_loss, p=5)	RGB / built-in preprocess
Complex CNN (Ours)	Adam lr=1e-3	30	ES(val_loss, p=7) + ReduceLR(val_loss, f=0.2, p=4, min=1e-7)	Gray / ÷255 + augmentation

ES = EarlyStopping (restore_best_weights=True). ReduceLR = ReduceLROnPlateau.

A.5 Data Augmentation (Complex CNN Only)

Applied to training generator only. Validation and test: rescale=1./255 only.

Parameter	Value	Rationale
rescale	1./255	Normalize to [0, 1]
rotation_range	15	Random rotation ±15°
width_shift_range	0.1	Horizontal shift ≤10% of width
height_shift_range	0.1	Vertical shift ≤10% of height
zoom_range	0.1	Random zoom ±10%
horizontal_flip	True	Expressions broadly symmetric
fill_mode	"nearest"	Fill pixels after transformation

A.6 Complex CNN — Full Layer Specification

Input: (48, 48, 1). All Conv2D: kernel_size=(3,3), padding="same". Total trainable params: ~8.3M.

Block	Filters	Kernel	Padding	Norm + Activation	Pooling	Dropout
Block 1 (×2)	64	3×3	same	BatchNorm + ReLU	MaxPool(2,2)	0.25
Block 2 (×2)	128	3×3	same	BatchNorm + ReLU	MaxPool(2,2)	0.25
Block 3 (×2)	256	3×3	same	BatchNorm + ReLU	MaxPool(2,2)	0.25
Block 4 (×2)	256	3×3	same	BatchNorm + ReLU	MaxPool(2,2)	0.25
Block 5 (×1)	512	3×3	same	BatchNorm + ReLU	GlobalAvgPool	0.50
Dense Head	—	—	—	Dense(256,relu) → BatchNorm → Dropout(0.5)	—	—

Output	—	—	—	Dense(4, softmax)	—	—

A.7 Learning Rate Schedule — Complex CNN

Epochs	Learning Rate	Event
1–12	1e-3 (0.001)	Initial rate — rapid convergence
13	→ 2e-4 (0.0002)	ReduceLROnPlateau triggered (factor 0.2)
14–26	2e-4 (0.0002)	Steady improvement phase
27	→ 4e-5 (0.00004)	ReduceLROnPlateau triggered (factor 0.2)
28–30	4e-5 (0.00004)	Fine-tuning — best val_loss at epoch 30

A.8 Transfer Learning Setup (Frozen Base)

Architecture	Load Arguments	Frozen Params	Preprocessing
VGG16	weights="imagenet", include_top=False	14,714,688	VGG16 preprocess_input (channel-mean subtraction)
ResNet50V2	weights="imagenet", include_top=False	23,564,800	ResNet50V2 preprocess_input (scale to [-1,1])
EfficientNetB0	weights="imagenet", include_preprocessing=True	4,049,571	Built-in (no external preprocess call needed)

Custom head (identical for all TL models): GlobalAveragePooling2D → Dense(256, relu) → Dropout(0.5) → Dense(4, softmax). Input grayscale images replicated to 3 channels via Lambda(tf.image.grayscale_to_rgb). No base layer unfreezing was performed.