IEEE ACCESS · VOL.13 · 2025 · RESEARCH PRESENTATION

# DRIVER DROWSINESS DETECTION

Using Deep Learning & Computer Vision

BASED ON THE PAPER

**Deep Learning-Based Drowsiness Detection System for Driver's Safety**

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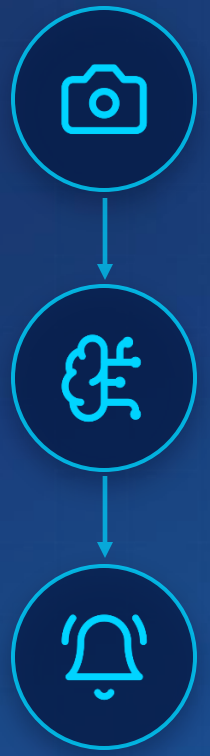
01 · OVERVIEW

# Introduction

- Drowsiness silently degrades reaction time and judgment
- A camera-based AI can watch what drivers can’t feel
- **The paper proposes a real-time detection system**
- Deep learning + computer vision work together
- **Runs on standard hardware — no special sensors**
- Goal: high accuracy and fast inference at once

HOW THE IDEA WORKS



**Camera watches the driver**

**Deep model reads eyes & mouth**

**Drowsiness flagged instantly**

02 · THE HUMAN COST

# Why Driver Drowsiness Is a Serious Problem

**100K+**

crashes every year in the US alone — National Safety Council

**~1,000**

lives lost annually to drowsy driving — National Safety Council Council

**Microsleep = 100 m blind**

A few seconds at highway speed with eyes closed

**No roadside test exists**

Impairs like alcohol — but can’t be measured at a stop

**Drivers underestimate it**

Prevention must be automatic, not self-reported

03 · THE RESEARCH GAP

# Problem Statement

Accurate models are heavy & slow — or or need costly hardware

**ACCURACY**

Body sensors (EEG-style) work — but are intrusive for drivers

?

**REAL-TIME SPEED**

**LOW-COST HARDWARE**

**The gap: can deep learning deliver all three — simultaneously?**

04 · WHAT THE AUTHORS SET OUT TO DO

# Research Objectives

01 Build a real-time driver drowsiness detection system system

02 Design a custom CNN + SVM classification pipeline

03 Develop a lightweight transfer-learning model on a model on a pre-trained backbone

04 Optimize split ratios, dropout rates & L2 regularization

05 Evaluate on two public datasets — Kaggle 4-class & MRL

06 Compare models via precision, recall, F1 & confusion matrices

# Dataset Information

DATASET 1 · KAGGLE DROWSINESS

## Four classes — eyes and mouth behavior

- Open Eyes
- Closed Eyes
- Yawn
- No Yawn

DATASET 2 · MRL EYE DATASET

**37**

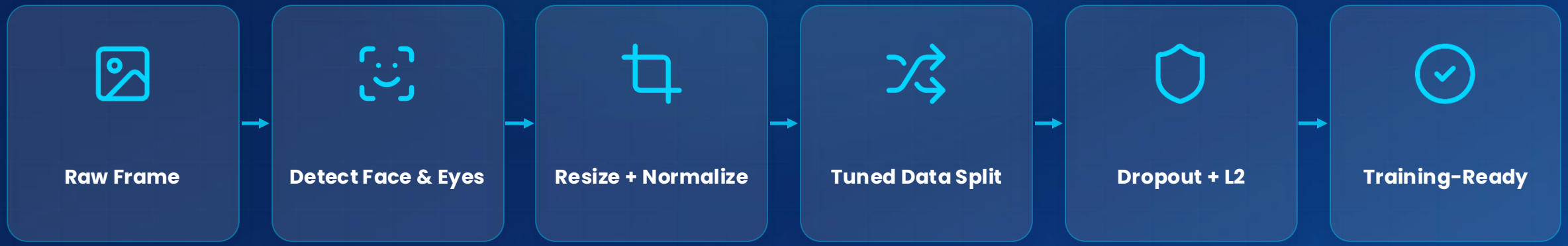
**human subjects**

Diverse eye images from many people → person-to-person person robustness

06 · DISCIPLINE BEFORE LEARNING

# Data Preprocessing

Clean data in → clean results out. Every frame passes through this pipeline before training.




### Tuned, not defaulted

Split ratios, dropout rates & L2 strength were optimized as design design choices

### Generalize, don't memorize

Regularization keeps validation accuracy nearly equal to accuracy

07 · TWO PHILOSOPHIES, ONE GOAL

# Deep Learning Architecture

## Model A · Custom CNN + SVM

- Input Image
- Convolutional Blocks
- Learned Feature Vector
- **SVM Classifier**
- Alert / Drowsy Output

*Hand-crafted precision · stabilized with dropout + L2*

VS

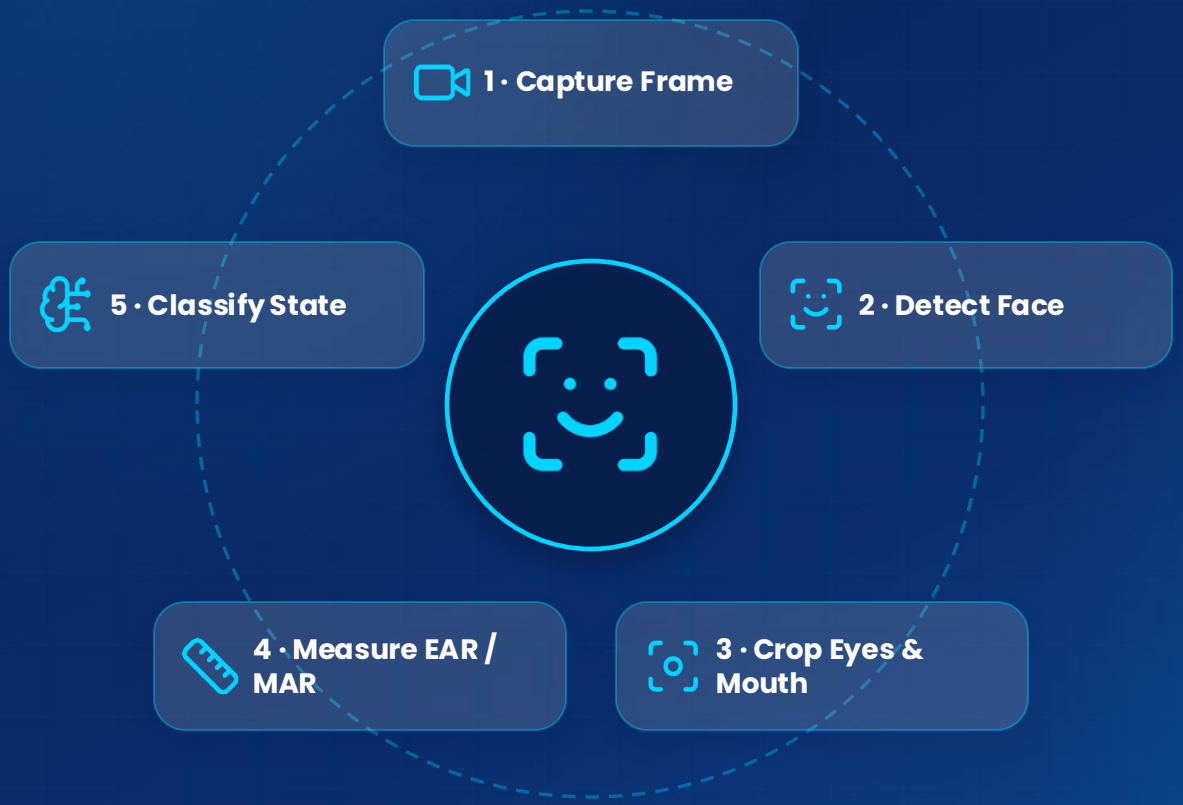
## Model B · Transfer Learning

- Input Image
- **Pre-trained Backbone (reused)**
- Lightweight New Head
- Fine-tuned Weights
- Alert / Drowsy Output

*Leveraged knowledge · faster training, real-time ready*

08 · GEOMETRY MEETS INTELLIGENCE

# Computer Vision Workflow




*continuous loop — many frames per second*

**EAR** Eye Aspect Ratio

Ratio collapses when eyes close → sleepiness signal

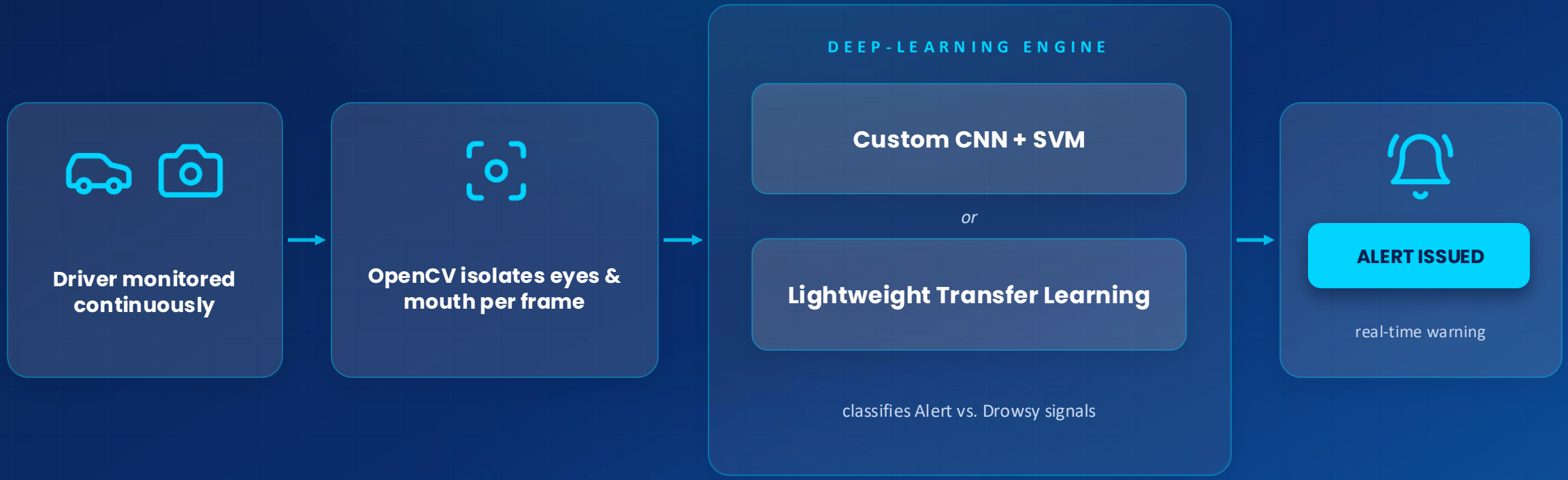
**MAR** Mouth Aspect Ratio

Ratio spikes during a yawn → fatigue signal

**OpenCV finds the where.**
**Deep learning gives the verdict.**

09 · THE COMPLETE SYSTEM

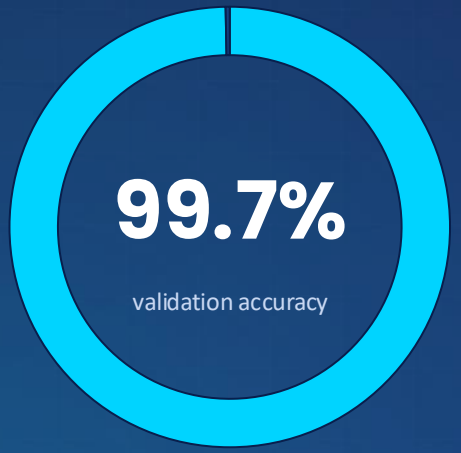
# Proposed Method — End-to-End




**Camera in → life-saving signal out.** **Real time, on standard hardware.**

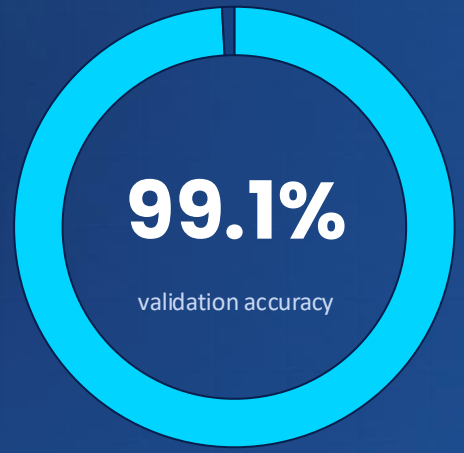
# Experimental Results

## Custom CNN + SVM




Training accuracy: 100%
Optimized split · dropout · L2

## Transfer Learning Model

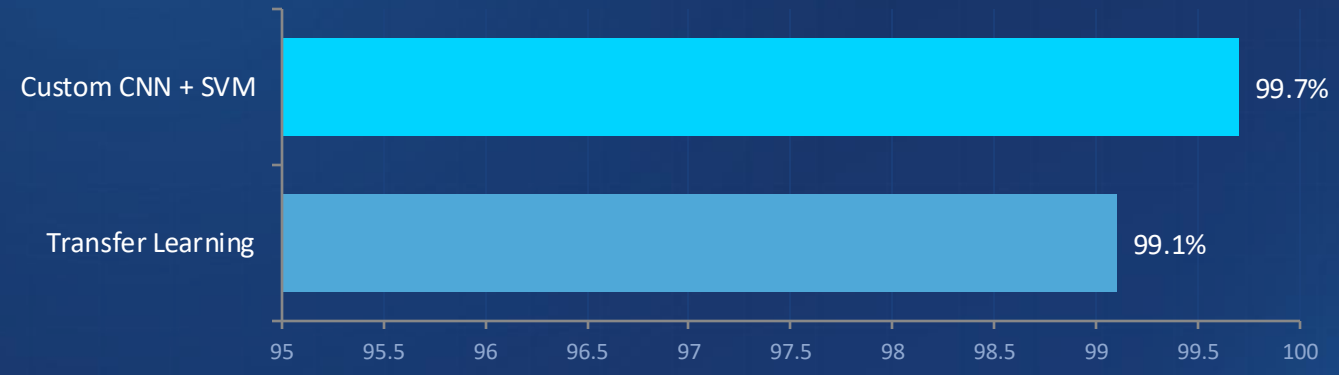



Training accuracy: 99.4%
Pre-trained backbone · fast training

**Validated with loss curves · confusion matrices · precision · recall · F1-score**

# Performance Comparison

## Validation accuracy — a photo finish




**Accuracy champion**
Custom CNN + SVM · 99.7%

**Efficiency champion**
Transfer learning · fast to train

| Aspect | Custom CNN + SVM | Transfer Learning |
|---|---|---|
| Training accuracy | 100% | 99.4% |
| Training approach | Built from scratch | Pre-trained backbone |
| Evaluated with | Precision · Recall · F1 | Precision · Recall · F1 |

12 · A BALANCED VIEW

# Advantages & Limitations

## ADVANTAGES

- ~99%+ validation accuracy — on both datasets
- Real-time on standard hardware — affordable to deploy
- Non-intrusive — camera only, no body sensors
- Dual-model design → deployment flexibility

## LIMITATIONS · CRITICAL APPRAISAL

**Curated datasets ≠ real cabins**
Night light, sunglasses & occlusion make real driving harder harder

**37-subject MRL cohort**
Wider demographic validation would strengthen the

*Not flaws — the natural frontier every lab-to-road system must cross.*

# Future Work

**Paper's stated direction:** broader road-safety deployment

1
**In-vehicle alerting**
Audio & haptic warnings

2
**Real driving conditions**
Night · glasses · motion

3
**Edge deployment**
In-car chips & mobile

4
**Diverse cohorts**
Larger subject studies

5
**ADAS integration**
Smart-vehicle ecosystems

**99.7%**

peak validation accuracy

**Real-Time**

frame-by-frame inference

**Standard HW**

a camera is enough

# “Technology that stays awake, so drivers stay alive.”

Accurate + real-time + affordable — this study shows the trade-off is solvable.

# THANK YOU

Questions & Discussion Welcome


REFERENCE

Dixith, S. V., Jadhav, S., Kim, Y., & Jayakumar, N. (2025). Deep Learning-Based Drowsiness Detection System for System for Driver's Safety. *IEEE Access, 13*, 154080–154102.
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