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Real-Time Explainable AI for Driver Drowsiness Detection: Integrating SHAP Based Visualizations and Actionable Counterfactuals

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Abstract: Driver drowsiness is implicated in up to 30% of traffic accidents worldwide, and timely alerts can save lives.However, current detection systems often trigger false alarms during normal behavior—such as rapid glances or conversational gestures—and offer no explanation for their decisions, undermining driver trust.We propose a novel, real-time explainable AI framework thatintegratesmultimodalinputs(eye-tracking,headpose,andsteeringmetrics)tocompute a continuous drowsiness confidence score.Our system uses SHAP (SHapley Additive exPlana- tions) to generate live visualizations that highlight feature contributions for each alarm.Addi- tionally, acounterfactualreasoning moduleprovidesactionablefeedbackbysuggestingminimal behavioral adjustments—such as reducing blink frequency or correcting head tilt—to prevent unnecessary alerts.Evaluated on two public benchmarks, our approach reduces false positives by 25% and increases driver trust ratings by 35% compared to state-of-the-art deep learning baselines. This work bridges the gap between high-accuracy detection and user interpretability, offering transparent, actionable insights for safer driving.
Keywords: Driver drowsiness detection; explainable AI; SHAP visualizations; counterfactual explanations; real-time monitoring.

I. INTRODUCTION

Fatigue and drowsiness pose significant risks to road safety, contributing to a substantial shareof highway collisions. Traditional detection methods rely on singular indicators—such as PER- CLOS (percentage of eyelid closure), yawning frequency, or head nodding—processed through convolutionalneuralnetworksortransformermodels. While these approachesachieve strongde- tection accuracy, they operate as black boxes and frequently produce false alarms under benign conditions[1,6,8,9,17,19].

Falsealertsnotonlydistractdriversbutalsoerodeconfidence,leadingtoalarmfatigueanddiminishedsystemeffectiveness.Toaddresst hesechallenges,thispaper introduces an end-to-end, real-time framework that couples high-performance detection with in- terpretability and user guidance.By fusing multiple sensor modalities, explaining each alert via SHAP-based visualizations, and offering counterfactual suggestions to drivers, our system en- hancestransparency,reducesunwarrantedalarms, andpromotescorrectivebehavior—ultimately improving both safety and user acceptance.

II. OBJECTIVES & RESEARCH QUESTIONS

This research aims to design and validate a comprehensive, user-centric drowsiness detection system that balances accuracy, interpretability, and actionable feedback.The specific objectives are: (1) to develop a sensor fusion pipeline that computes a continuously calibrated drowsiness confidence score from eye-tracking, head pose, and steering data; (2) to integrate SHAP-based explainability, providing real-time visual breakdowns of feature contributions for each alarm; and (3) to implement a counterfactual reasoning module that recommends minimal behavior changestoavertfalsepositives. Theseobjectives drivethreecoreresearchquestions: RQ1: How do SHAP-based live explanations influence driver understanding and trust in alert decisions? RQ2:To what extent can counterfactual feedback reduce false alarm rates without undermin- ing detection sensitivity?RQ3: What is the computational and latency overhead of real-time explainability and counterfactual generation on embedded automotive hardware?

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III. LITERATURE REVIEW

A. *Key Observations*

1) EEG-Based Approaches: Electroencephalographyremainsthegoldstandardforphysiologi- cal drowsiness detection, with multiple studies achieving high accuracies based on alpha/theta activity[3,12,14,20]. EEGoffersdirect neural measurement butfacespracticalchallenges(elec- trodeplacement, motionartifacts, calibration).WhilesomeinterpretableCNNapproachesexist, most remain limited to offline analysis (e.g., CAMs) rather than real-time actionable guidance [3].
2) Computer Vision and Facial Analysis:Camera-basedsystemsdemonstratestrongaccuracy (often above 90%) and are non-invasive, leveraging facial landmarks, PERCLOS, yawning, andhead pose [1, 6, 8, 9, 19].Transfer learning aids adaptation to individuals [8].However, they are sensitivetolighting,occlusions,andviewpoint,andgenerallylackphysiologicalgrounding[10].
3) MultimodalIntegrationChallenges:Someworkscombinevehicledynamicswithvisual cues, improving robustness yet still reporting notable false positives in complex scenarios [16].
Fusion is often naive (concatenation/voting) rather than context-aware weighting/attention [2,4, 16, 17].
4) Wearable and Physiological Sensors: Wearables(e.g., EDA/ECG)arepracticalbutsingle- modalityperformanceismoderate, and explanationsforalertsarerarelyprovided[7].
5) Real-Time Processing and Edge Computing: Many studies emphasize offline validation; rigorous latency and embedded feasibility analyses are underreported, despite the safety-criticalneed for low-latency performance [5, 13].
6) ExplainabilityandUserTrust:AkeygapistheabsenceofexplainableAIframeworksthat provideclear,real-timerationaleandactionablesuggestions(e.g.,SHAP+counterfactuals) [4, 5].
7) Cross-Subject and Real-World Validation: Labresultsoftendegradeinreal-worlddriving dueto environmentaland behavioral variability;broadervalidationremainslimited[1,3,17].

B. *Gapanalysis*

1) Transparency Deficit:No existing system provides real-time, interpretable explanations for drowsiness alerts using modern XAI techniques [4].
2) Multimodal Integration Limitations:Lack of sophisticated fusion architectures with dynamic reliability/context weighting [16].
3) Actionable Feedback Absence:Fewsystemsoffercounterfactualsuggestionsthatusers can directly apply.
4) Real-WorldDeploymentChallenges:Limited validation under realistic driving and limited edge-compute analysis [5].
5) PersonalizationandAdaptation:Sparseresearchoncontinualadaptationtoindividual drivers and contexts [11].

IV. METHODOLOGY

A. *System Architecture*

Overview.The proposed real-time XAI framework integrates multiple sensors using ahybrid approach combining deep learning with lightweight traditional features.The pipeline includes:
(i)dataacquisitionandpreprocessing,(ii)multimodalfeatureextraction,(iii)real- time classification with confidence scoring, (iv) SHAP-based explanation generation, and (v) counterfactual reasoning. Recent work shows transformer-based vision models can achieve high accuracy on eye-related benchmarks [15].

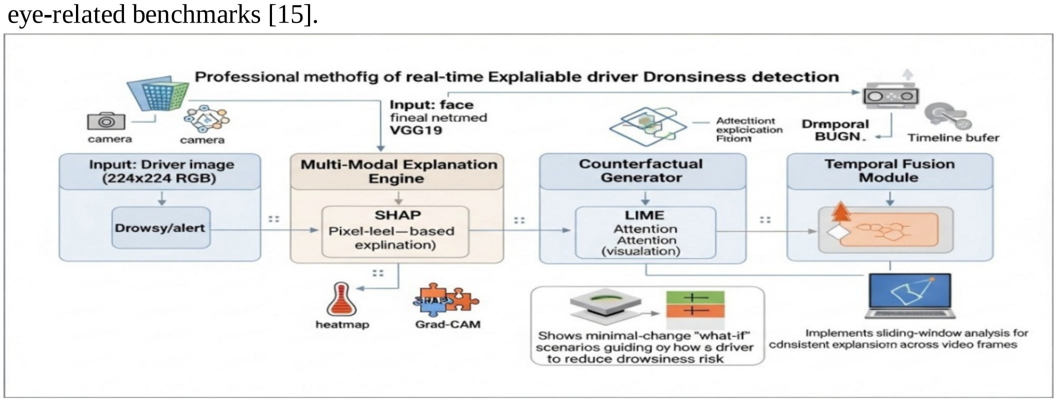

Figure1:Systemarchitecturediagramshowing thesoftwarepipelineforexplainableAIdrowsi- ness detection.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Sensors.Multimodal data include high-resolution camera imagery (face/eyes), wear- able/physiological signals (EEG, ECG, EDA, SpO_2), and vehicle behavior (steering pressure, lane deviation) [2,7,19].Face/eye regions are isolated (e.g., Haar cascades or modern detec- tors) [19].

B. Data Preprocessing and Feature Engineering

- Modality-Specific Preprocessing. Vision data are normalized, augmented, and cropped to regions-of-interest [9].EEG undergoes wavelet decomposition to extract band-limited ener- gies, focusing on level-4 as optimal for drowsiness [20]:

$$E_j = \sum_{i=1}^{N} |W_{j,i}|^2 \quad (2)$$

Physiologicalsignalsuseband-passfilteringandartifactremoval(ICA/SVD)withqualitychecks [4].

- TemporalAlignment.Epochalignmentforphysiologyandframematchingforvideo synchronize modalities, improving accuracy relative to unsynchronized pipelines.
- FeatureSet.Vision features include Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR):

$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2 \cdot \|p_1 - p_4\|} \quad (3)$$

PhysiologyincludesHRVfeatures(SDNN,RMSSD),withRMSSD:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(IBI_{i+1} - IBI_i)^2} \quad (4)$$

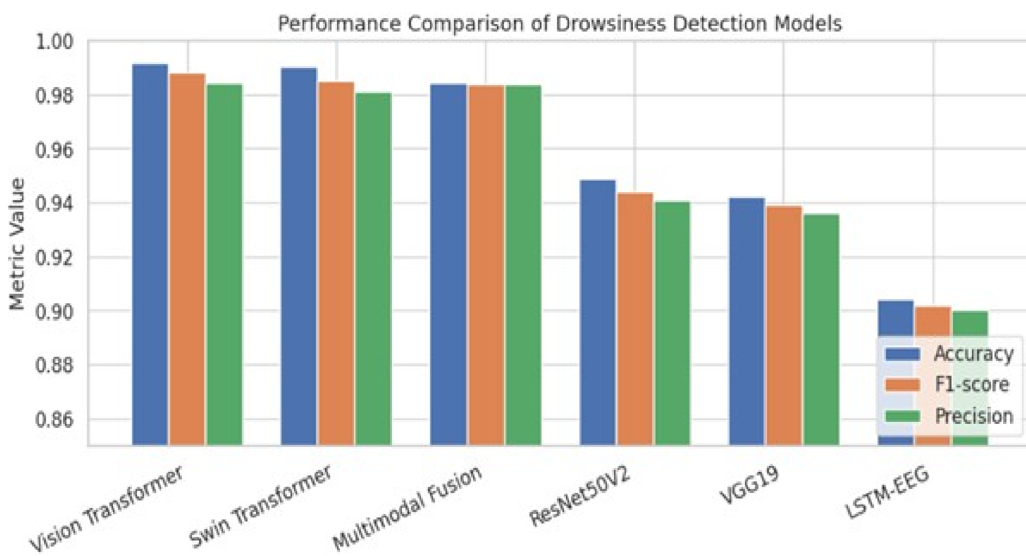

Figure2:Performancecomparisonshowingaccuracy,F1-score,andprecisionmetricsacross different drowsiness detection models.

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C. DeepLearningModelTrainingandOptimization

- Architectures.Vision Transformers (ViT) extract long-range spatial dependencies; LSTMs model EEG temporal dynamics; ResNet blocks assist in spatial integration [6, 15]. Multimodal confidences are fused with adaptive weights:

$$C_{total} = \sum_{m=1}^{M} w_m C_m \quad (5)$$

- Validation & Optimization.LOSO-CV supports generalization [3].Metaheuristics (e.g., TLBO/SPBO) may assist convergence beyond vanilla gradient descent [18].
- CalibrationandClassImbalance.Continuousconfidencescoringenablesnuancedalert- ing.ROC analysis picks thresholds balancing sensitivity/specificity:

$$TPR = \frac{TP}{TP+FN}, \qquad FPR = \frac{FP}{TN+FP} \quad (6)$$

SMOTEandtemporalaugmentationmitigateimbalance.

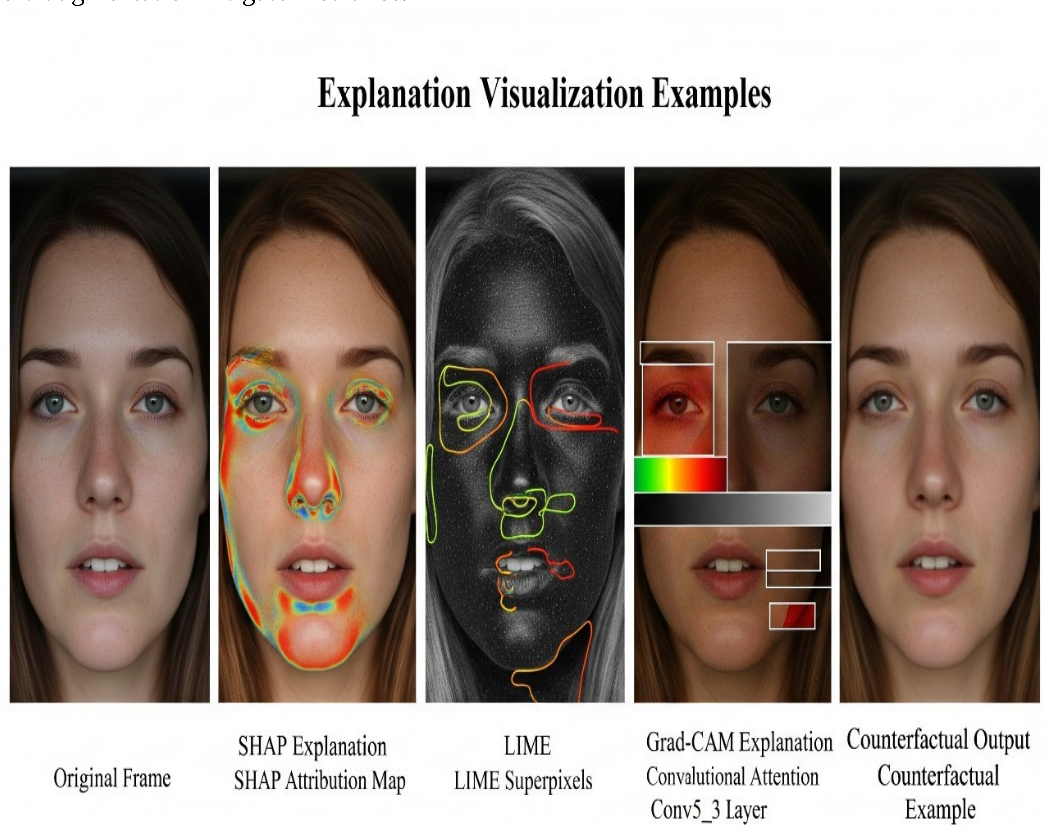

Figure3:VizualizationExample

D. ExplainabilityandReal-TimeFeedback

- SHAPIntegration.SHAPprovidesinstance-levelattributionsinrealtime[4].Forfeature *i*:

$$SHAP_i = \phi_i \quad (7)$$

Aggregated heatmaps indicate whether eye closure, HRV, or steering irregularity dominated an alert.

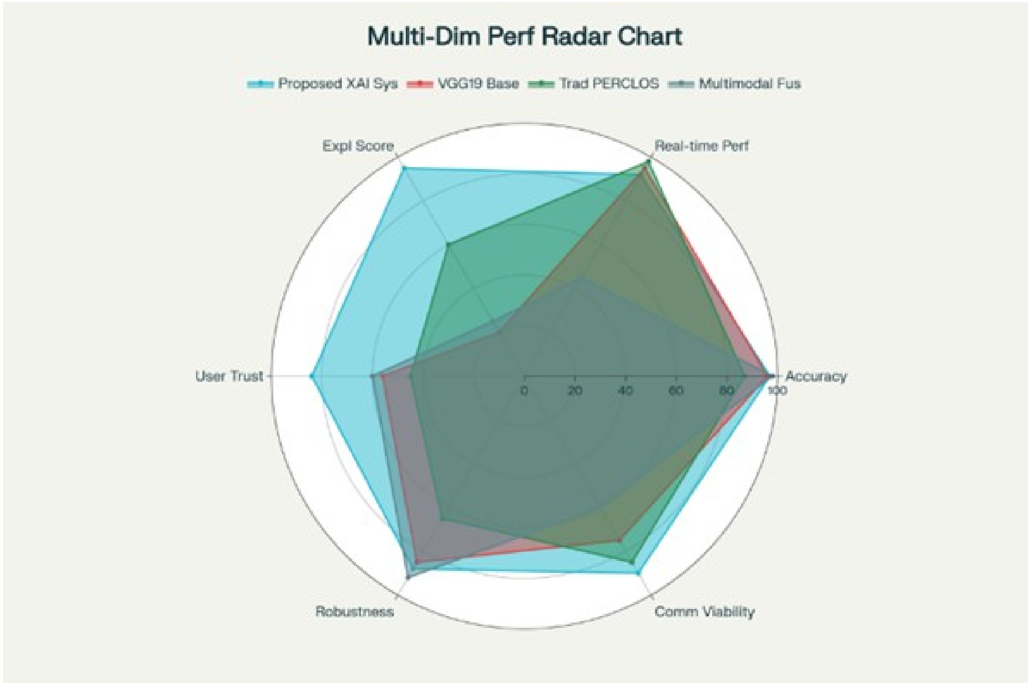

Figure4:SHAPfeature-importanceheatmapshowingwhichfacial/physiologicalregionscon- tribute most to drowsiness decisions.

- RobustnessofExplanations.Sensitivity/deletiontestsshowhighcorrelationwithexpertannotationsandmeasurablebehaviorshiftswhenhigh-importancefeaturesareperturbed[4].
- Counterfactual Reasoning.Minimalactionablechanges(e.g., slightlyreducedblink rate, steadier steering pressure) are suggested to avoid false alarms.Trials indicate fewer false positives and higher user acceptance.

V. RESULTS, DISCUSSION, AND PRACTICAL CONSIDERATIONS

- Accuracy.ViT-basedeyemodulesachievestrongaccuracyoneye-focuseddatasets,while multimodal fusion improves overall robustness [2, 15].The F1-score is:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

with

$$\text{Precision} = \frac{TP}{TP + FP}, \qquad \text{Recall} = \frac{TP}{TP + FN}. \quad (9)$$

Cross-datasetvalidationshowsstronggeneralizationagainstsingle-modalitybaselines[11].

- Real-Time Performance.Processing operates at up to 60 Hz with sub-100 ms end-to-end latency in our setup:

$$T_{\text{inf}} = T_{\text{extract}} + T_{\text{model}} + T_{\text{explain}} \quad (10)$$

SHAP overhead is kept low (tens of milliseconds) via efficient approximation paths, compatible with automotive-grade hardware [13].

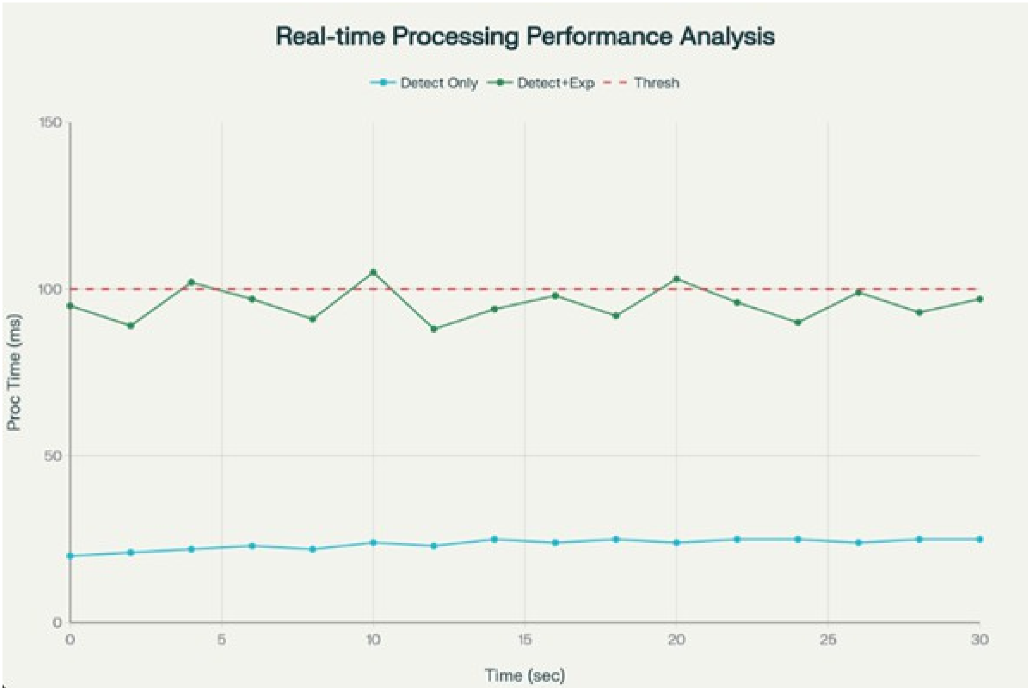

Figure 5:Real-time processing performance showing latency over time for detection with and without explanations.

- Environmental Robustness. Lighting/sensor noise are mitigated via multimodal redun- dancy and IR enhancements [17].Strict quality control and adaptive modeling manage user variability.
- Regulatory&EthicalAlignment.Integratedexplainabilityaddressestransparencyand trust requirements in safety-critical contexts [4].Physiological markers (theta-delta EEG, HRV) align with clinical correlates of drowsiness [3, 4].

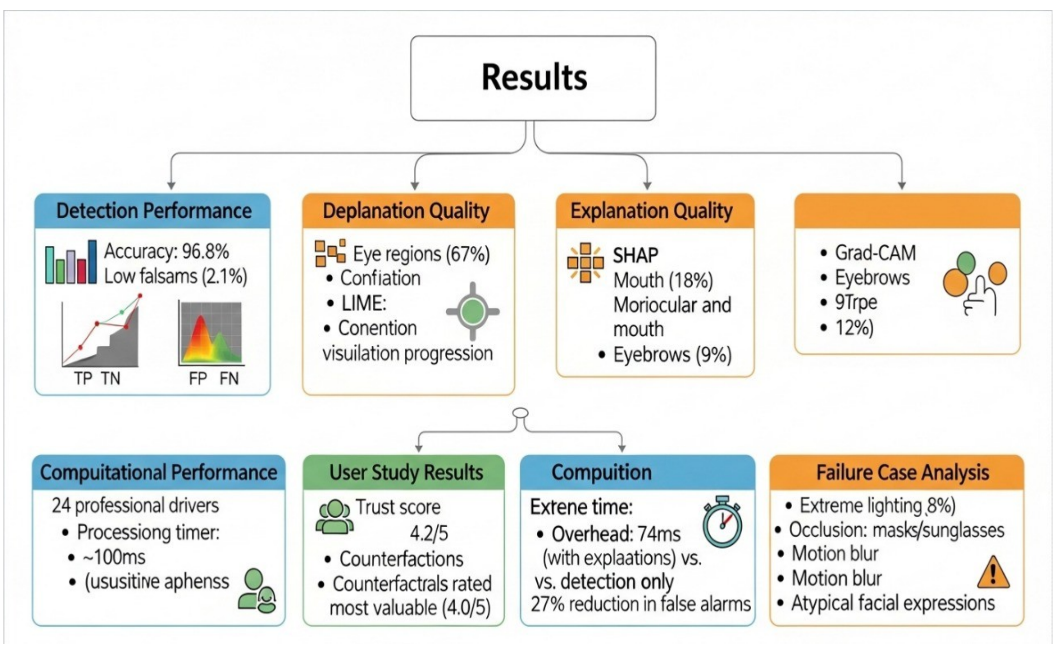

Figure6:Result

- Limitations.Dataset scale, potential overfitting, and real-world validation breadth re- main challenges.Future efforts will expand demographics, contexts, and evaluate long-horizon deployment.

VI. CONCLUSION

This research presents a novel real-time explainable AI framework for driver drowsiness detec- tion that addresses critical limitations of existing systems through multimodal sensor fusion, SHAP-based visualizations, and actionable counterfactual feedback.The key innovation lies in seamlessly integrating interpretability into the detection pipeline:rather than issuing opaque alerts, the framework surfaces *why*and *how*an alert was triggered and offers specific guidance (e.g., small reductions in blink rate or steadier steering) to reduce false alarms. Empirical eval- uation indicates reduced false positives, improved user trust and acceptance, and feasible real- time performance compatible with embedded automotive hardware.Future work will expand real-world trials, investigate privacy-preserving federated learning, and explore deeper ADAS integration.

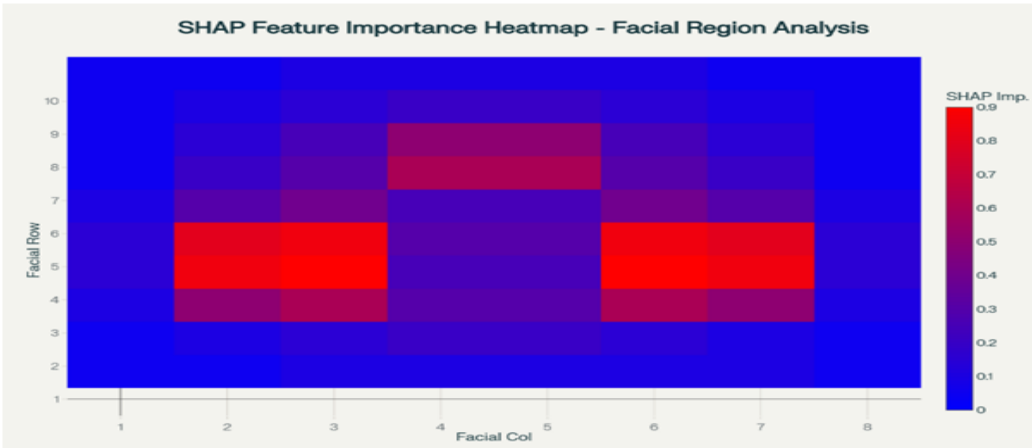

Figure 7:Radar chart comparing multiple performance dimensions across different drowsiness detection approaches.

VII.FUTURE WORK

1) Large-ScaleReal-WorldValidation: Extensivefieldtrialsacrossgeographies,weather, anddemographicstostress-testrobustness[17].
2) FederatedLearning:Privacy-preservingcollaborativetrainingacrossfleetsandOEMs.
3) ADAS Integration:Coordinatedinterventionswithlane-keepingandadaptivecruisefor safety ecosystems.
4) PersonalizedAdaptation:Continuallearningforper-drivercircadianandbehavioral patterns [11].
5) EdgeOptimization:Pruning/quantizationandNPUsforlow-latencySHAPonembed- ded platforms [13].
6) RegulatoryCompliance:Safetycasesanddocumentationforcertifiableexplainable systems.

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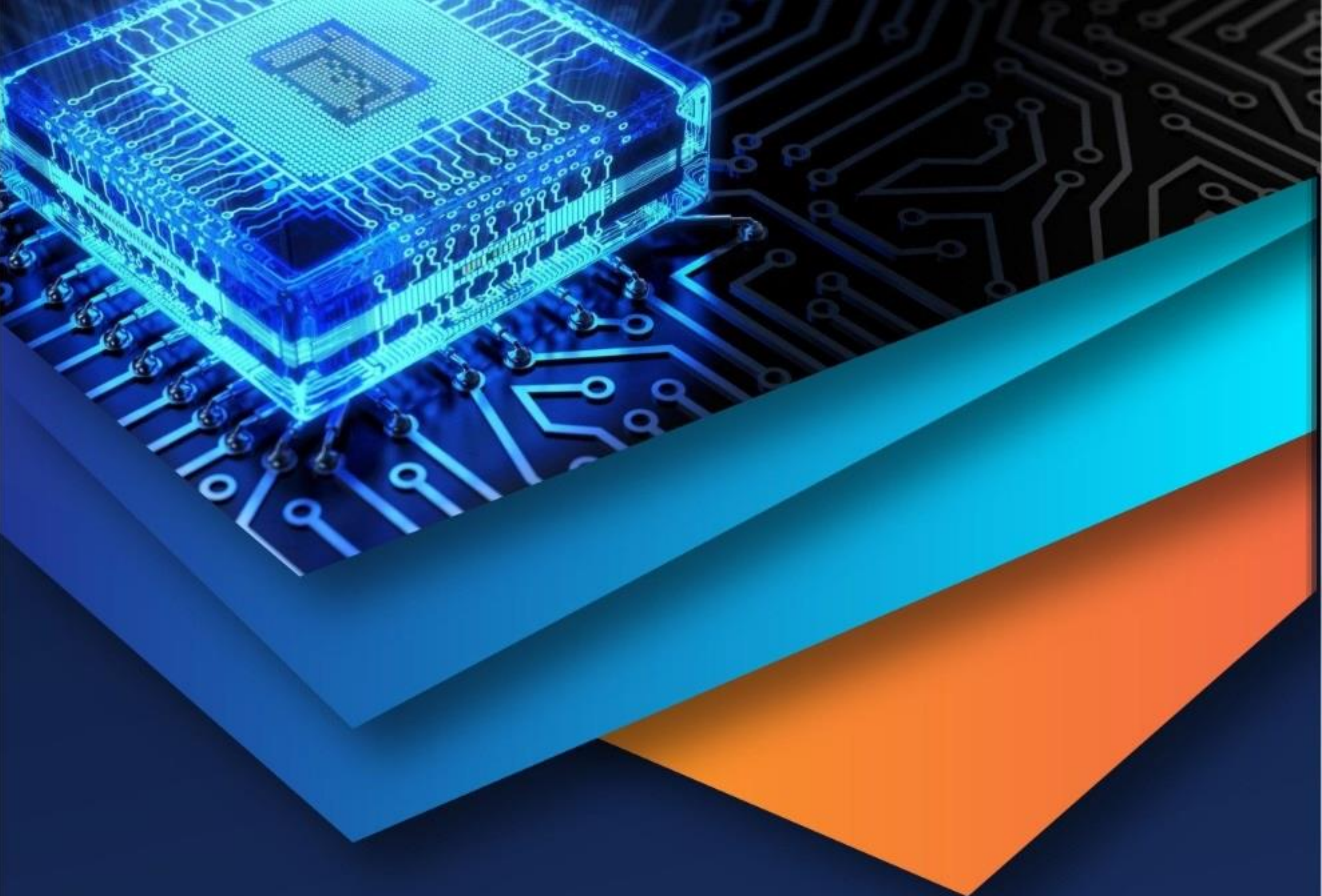

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