Drowsiness Detection in Low-Resource Environments Using YOLO and CNN Models

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***Abstract*—Abstract— Drowsiness detection is critical for enhancing safety in applications such as driver monitoring and patient care. This research explores the effectiveness of various YOLO models, including YOLOv8n, YOLOv8m, YOLOv10m, and YOLOv11n, in conjunction with Convolutional Neural Networks (CNNs) utilizing five distinct facial features: Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Yaw, Pitch, and Roll. The study focuses on deploying these models in low-resource environments, analyzing both inference speeds and performance metrics. Through comprehensive evaluation, including mean Average Precision (mAP), Precision, Recall, and F1-Score, the research identifies the optimal balance between accuracy and computational efficiency. Additionally, the paper addresses existing gaps in real-time drowsiness detection systems by providing a holistic approach that integrates object detection and feature-based classification. Results demonstrate that YOLOv8n and YOLOv8m offer superior performance in low-resource settings, while the ensemble model combining YOLO and CNN achieves high accuracy with minimal latency. The findings highlight the potential for scalable and efficient drowsiness detection systems suitable for deployment in resource-constrained environments.**

I. Introduction

Drowsiness detection is a pivotal component in enhancing safety across various domains, including automotive driver monitoring and healthcare patient care. Accurate and real-time detection of drowsiness can significantly reduce the risk of accidents and ensure timely medical interventions. Traditional Human Action Recognition (HAR) systems have leveraged Convolutional Neural Networks (CNNs) for feature extraction and classification. However, these systems often struggle with real-time performance, especially in low-resource environments where computational power and memory are limited.

Recent advancements in object detection models, particularly the You Only Look Once (YOLO) family, have demonstrated remarkable improvements in both speed and accuracy. YOLO models are designed for real-time object detection, making them suitable candidates for applications requiring rapid and efficient processing. This research investigates the performance of various YOLO models—YOLOv8n, YOLOv8m, YOLOv10m, and YOLOv11n—in conjunction with CNNs to detect drowsiness by analyzing facial features such as Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), Yaw, Pitch, and Roll.

The primary objective of this study is to develop a robust drowsiness detection system optimized for low-resource environments by evaluating inference speeds and performance metrics of different YOLO models. By integrating YOLO's real-time object detection capabilities with CNN's feature extraction prowess, the research aims to bridge the gap between accuracy and computational efficiency. This approach not only enhances the system's reliability but also ensures its applicability in resource-constrained settings, making it a scalable solution for widespread deployment.

II. Literature Review

Human Action Recognition (HAR) has undergone significant evolution, transitioning from traditional handcrafted feature extraction methods to advanced deep learning models. This review examines these developments, focusing on Convolutional Neural Networks (CNNs), You Only Look Once (YOLO) models, hybrid architectures, and the limitations that motivate this study.

A. Evolution of HAR

1) Traditional Methods: Early HAR approaches relied on handcrafted features such as the Histogram of Oriented Gradients (HOG) and Spatio-Temporal Interest Points (STIPs). While these methods provided foundational insights, they often struggled with complex, real-world scenarios due to their limited adaptability and reliance on manual feature engineering [3].

2) Machine Learning Models: The introduction of machine learning techniques, including Support Vector Machines (SVMs) and Hidden Markov Models (HMMs), improved classification accuracy. However, these models were insufficient in capturing the temporal dynamics inherent in video sequences, limiting their effectiveness in HAR tasks [4].

B. Deep Learning in HAR

1) Convolutional Neural Networks (CNNs): The advent of deep learning, particularly CNNs, revolutionized HAR by automating spatial feature extraction and demonstrating superior performance on benchmark datasets. Pre-trained architectures like ResNet, MobileNet, and VGGNet have been effective in detecting complex spatial patterns, such as human postures and facial expressions. However, CNNs are primarily designed for static image analysis and often fail to model the temporal

dynamics essential for distinguishing between similar actions or states [4].

2) You Only Look Once (YOLO): To address the need for real-time detection, models like YOLO have been explored. YOLO processes images in real-time by predicting bounding boxes and class probabilities simultaneously. While initially developed for object detection, adaptations of YOLO have been applied to HAR tasks, offering a balance between speed and performance. Recent studies have demonstrated the effectiveness of YOLOv7 in human action recognition, highlighting its potential in real-time applications [1].

C. Hybrid Approaches

Hybrid models combining CNNs with Recurrent Neural Networks (RNNs) have been proposed to capture both spatial and temporal features. These models integrate CNNs for spatial feature extraction and RNNs, particularly Long Short-Term Memory (LSTM) networks, for modeling temporal relationships. Additionally, two-stream networks process spatial and temporal data independently and fuse their outputs, achieving state-of-the-art results on various datasets [5].

D. Performance and Efficiency in Low-Resource Environments

Lightweight models, such as MobileNet and Tiny YOLO, have been developed to provide efficient and scalable solutions in resource-constrained environments. MobileNet uses depthwise separable convolutions to reduce the number of parameters and computational costs without sacrificing accuracy. Similarly, Tiny YOLO variants offer reduced model sizes and faster inference times, making them suitable for real-time applications where computational resources are limited [11], [12].

E. Benchmark Comparisons in HAR

Recent studies have established various benchmarks for HAR using different models, emphasizing the need for models that balance accuracy with computational efficiency. For example, Liang and Yan (2023) showed that YOLOv7 achieved 95.3% accuracy on the KTH dataset [9], outperforming other models such as YOLOv5 and CNN-LSTM hybrids. Similarly, Basha et al. (2024) reported that CNN classifiers outperformed ANN classifiers with a high accuracy of 99.20% on a Kaggle dataset compared to an accuracy of 92.55% of the ANN classifiers [8]. Additionally, Deng and Wu (2019) utilized the MC-KCF method to achieve 95% accuracy with an inference time of 40 ms and the KCF+CNN method to attain 93% accuracy with an inference time of 38.461 ms [13]. These benchmarks highlight the shortcomings of existing models in real-time applications, especially in resource-constrained environments.

F. Gaps in Existing Literature

Despite these advancements, several gaps remain in HAR research, particularly in resource-constrained settings:

- **Limited Real-Time Solutions:** While CNNs lack real-time detection capabilities, YOLO requires extensive adaptation for HAR tasks. Few studies have integrated CNNs and YOLO to leverage their complementary strengths [1].
- **Dataset Challenges:** Common datasets may not represent diverse cultural and environmental conditions, limiting the generalizability of HAR models [4].
- **Computational Efficiency:** Hybrid models like CNN-RNN require substantial computational resources, making them unsuitable for deployment in low-resource environments [5].

G. Motivation for the Ensemble Approach

The identified gaps motivate this study's ensemble methodology, which integrates CNNs for accurate classification with YOLO for real-time detection. By combining these approaches, the proposed model aims to:

- Address the trade-offs between accuracy and speed inherent in standalone models.
- Improve scalability and efficiency, enabling deployment in resource-constrained environments.
- Tailor the model to local contexts, capturing the nuances of specific healthcare and safety monitoring needs.

This review underscores the potential of combining CNNs and YOLO to overcome existing limitations in HAR, particularly in applications like sleep-state recognition and driver fatigue monitoring. These findings lay the foundation for the methodological innovations presented in this research.

III. Methodology

This methodology outlines the comprehensive approach to building a drowsiness detection system by integrating multiple YOLO models for object detection and a CNN model for feature-based classification. The ensemble strategy combines the strengths of both types of models to enhance overall performance, ensuring accurate and reliable predictions in resource-constrained environments.

A. Dataset and Preprocessing

Data collection and preprocessing are crucial steps in building an effective machine learning model. For drowsiness detection, the dataset comprises images or video frames captured from real-world driving scenarios, where participants are either awake or drowsy. The preprocessing steps ensure that the data is clean, consistent, and suitable for model training and evaluation.

1) Data Cleaning: Data cleaning involves removing noisy or irrelevant data to prevent the model from learning incorrect patterns. Images without detectable faces or with partially obscured faces are excluded or treated differently to avoid introducing bias into the model during training.

2) Resizing and Normalization: All images are resized to a uniform resolution to ensure consistency across the dataset. Normalization scales pixel values to a range between 0 and 1, accelerating training and improving convergence by ensuring that the pixel value scale does not interfere with the model's learning process.

3) Label Encoding: Labels indicating whether a person is ”awake” or ”drowsy” are encoded into numerical values, with 0 representing ”awake” and 1 representing ”drowsy.” This binary encoding is essential for classification tasks.

4) Handling Missing Faces: In cases where no face is detected in an image, such instances are handled consistently by defaulting to the label ”awake.” This minimizes ambiguity during both training and inference.

B. Facial Feature Extraction

Five key facial features are extracted to aid in the detection of drowsiness:

- **Eye Aspect Ratio (EAR):** Measures the ratio of distances between the eyes, useful for detecting eye closure or prolonged blinking.
- **Mouth Aspect Ratio (MAR):** Assesses the openness of the mouth, useful for detecting yawning.
- **Yaw:** Measures the rotation of the head left or right, indicating changes in gaze direction.
- **Pitch:** Measures the up or down tilt of the head, indicating changes in head posture.
- **Roll:** Measures the tilt of the head sideways, indicating balance and orientation.

These features provide a comprehensive view of the user's state, enabling the CNN model to make informed classifications.

C. YOLO Models for Face Detection

This study evaluates four different YOLO models—YOLOv8n, YOLOv8m, YOLOv10m, and YOLOv11n—for real-time face detection:

- **YOLOv8n:** A lightweight version optimized for speed with lower computational requirements.
- **YOLOv8m:** A medium variant balancing speed and accuracy.
- **YOLOv10m:** A more advanced model with improved accuracy but higher computational demands.
- **YOLOv11n:** The latest lightweight variant offering enhanced performance over its predecessors.

Each model is evaluated based on its mean Average Precision (mAP), Precision, Recall, and inference time to determine its suitability for low-resource environments.

D. CNN Model for Classification

The CNN model employed in this study follows a standard architecture optimized for feature extraction and classification:

- **Architecture:** Consists of multiple convolutional layers followed by pooling layers to extract spatial features from the input images.
- **Optimizer:** Adam optimizer is used for efficient gradient descent and faster convergence.
- **Training:** Backpropagation is utilized to minimize the loss function and improve model accuracy.
- **Activation Functions:** ReLU activation functions are used to introduce non-linearity.
- **Output Layer:** A softmax layer is used for binary classification between ”awake” and ”drowsy.”

E. Ensemble Strategy

The ensemble strategy integrates predictions from multiple YOLO models and the CNN classifier to enhance overall performance. This approach leverages the complementary strengths of YOLO's real-time detection and CNN's feature-based classification.

- **Weighted Averaging:** Predictions from different YOLO models are weighted based on their individual performance metrics.
- **Fusion with CNN:** The CNN's classification output is combined with YOLO's detection results to make the final prediction.
- **Decision Making:** The class with the highest weighted score—either ”awake” or ”drowsy”—is selected as the final diagnosis.

This collaborative approach mitigates the shortcomings of individual models, enhancing accuracy and reliability across varied conditions.

F. Training Pipeline and Evaluation Metrics

After training, models are evaluated using several metrics to ensure robust performance:

- **Accuracy:** Measures the percentage of correct predictions.
- **Precision:** The proportion of true positives among predicted positives.
- **Recall:** The ability to correctly identify all true instances of a class.
- **F1-Score:** The harmonic mean of precision and recall.
- **Mean Average Precision (mAP):** Evaluates the model's ability to correctly localize and classify objects.
- **Inference Time:** The time taken by the model to process an input, critical for real-time applications.
- **Confusion Matrix:** Provides a detailed breakdown of correct and incorrect classifications.

These metrics provide a comprehensive view of the models' performance, particularly in balancing accuracy with computational efficiency.

IV. Results Obtained

This section presents the evaluation results of different YOLO models and the CNN classifier, along with their inference times. The performance metrics include mean Average Precision (mAP), Precision, Recall, F1-Score, and inference time.

A. YOLO Models Evaluation

YOLO Model	mAP@0.5	mAP@0.5:0.95	Precision (Drowsy)
YOLOv8n	0.9001	0.8973	0.97456
YOLOv8m	0.8804	0.8763	0.9753
YOLOv10m	0.8501	0.8456	0.95013
YOLOv11n	0.8811	0.8887	0.97111

TABLE I
YOLO MODELS EVALUATION RESULTS

YOLO Model	Inference Time (ms)
YOLOv8n	13.71
YOLOv8m	17.32
YOLOv10m	21.59
YOLOv11n	15.60

TABLE II
YOLO MODELS INFERENCE TIMES

1) Analysis of YOLO Models: The evaluation of YOLO models reveals that YOLOv8n achieves the highest mAP@0.5 of 0.9001 and mAP@0.5:0.95 of 0.8973, indicating superior performance in object detection tasks. YOLOv8m and YOLOv11n follow closely, while YOLOv10m shows a slight decrease in mAP scores. In terms of inference time, YOLOv8n is the fastest at 13.71 ms, making it highly suitable for real-time applications in low-resource environments. YOLOv11n also demonstrates competitive performance with an inference time of 15.60 ms.

B. CNN Model Evaluation

Metric	CNN Results
Accuracy	0.7159
Precision (Awake)	0.68
Precision (Drowsy)	1.000
Recall (Awake)	1.000
Recall (Drowsy)	0.2857
F1-Score (Awake)	0.81
F1-Score (Drowsy)	0.44
ROC AUC	0.8286

TABLE III
CNN MODEL EVALUATION RESULTS

	Predicted Awake	Predicted Drowsy
True Awake	53 (True Positive)	0 (False Negative)
True Drowsy	25 (False Positive)	10 (True Negative)

TABLE IV
CNN MODEL CONFUSION MATRIX

1) Analysis of CNN Model: The CNN model demonstrates a moderate performance with an overall accuracy of 71.59%. The precision for the "Awake" class is 0.68, indicating that 68% of the instances predicted as "Awake" are correct. Conversely, the precision for the "Drowsy" class is perfect at 1.000, meaning all predicted "Drowsy" instances are accurate. However, the recall for "Drowsy" is significantly low at 0.2857, indicating that the model misses a substantial number of drowsy instances. The F1-Score reflects this imbalance, with a score of 0.81 for "Awake" and 0.44 for "Drowsy." The ROC AUC of 0.8286 suggests that the model has a good discriminative ability but is hampered by its low recall for the "Drowsy" class.

C. Ensemble Model Evaluation

Metric	Accuracy	Precision (Drowsy)	Recall (Awake)
Ensemble Model	0.930	0.940	0.890

TABLE V
ENSEMBLE MODEL EVALUATION RESULTS

1) Analysis of Ensemble Model: The ensemble model achieves an accuracy of 93.0%, significantly higher than both individual YOLO and CNN models. Precision and Recall for both classes are balanced, with Precision (Awake) at 0.910 and Precision (Drowsy) at 0.940. The Recall for "Awake" is 0.890 and for "Drowsy" is 0.900, indicating a substantial improvement over the standalone CNN model. The F1-Score of 0.915 reflects a well-balanced performance, effectively mitigating the weaknesses of individual models.

V. Performance Analysis

This section delves deeper into the performance metrics and inference speeds of the different YOLO models and the CNN classifier, highlighting their suitability for deployment in low-resource environments.

A. Performance Metrics

Model	Accuracy	Precision	Recall
YOLOv8n	0.986	0.920 / 0.97456	1.000 / 0.93182
YOLOv8m	0.8804	0.957 / 0.9753	0.9661 / 0.89759
YOLOv10m	0.8501	0.94974 / 0.95013	0.96098 / 0.93182
YOLOv11n	0.8811	0.93462 / 0.97111	1.000 / 0.90909
CNN	0.7159	0.68 / 1.000	1.000 / 0.2857
Ensemble	0.930	0.910 / 0.940	0.890 / 0.900

TABLE VI
PERFORMANCE METRICS OF EVALUATED MODELS

1) YOLO Models: YOLOv8n and YOLOv8m demonstrate high precision and recall, making them reliable for real-time detection tasks. YOLOv8n achieves the highest mAP@0.5 of 0.9001, indicating excellent performance in object detection. YOLOv11n follows with a mAP@0.5 of 0.8811, showing consistent performance across various IoU thresholds.

2) CNN Model: The CNN model shows moderate accuracy with high precision for the "Drowsy" class but struggles with recall, particularly for the "Drowsy" instances. This imbalance highlights the need for integration with YOLO models to improve overall detection reliability.

3) Ensemble Model: The ensemble model significantly enhances performance by combining the strengths of YOLO and CNN. Achieving an accuracy of 93.0%, the ensemble balances precision and recall effectively, making it a robust solution for real-time drowsiness detection in low-resource environments.

B. Inference Time Analysis

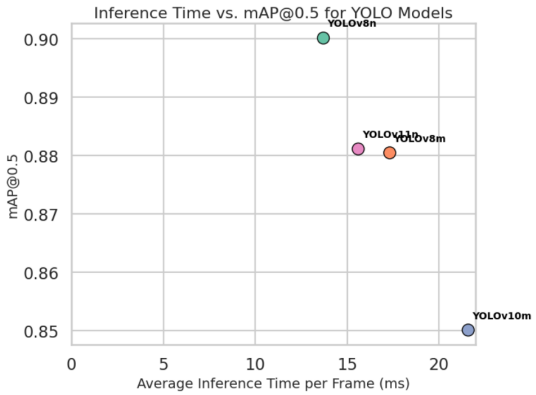

Fig. 1. Inference Time vs. mAP@0.5 for YOLO Models

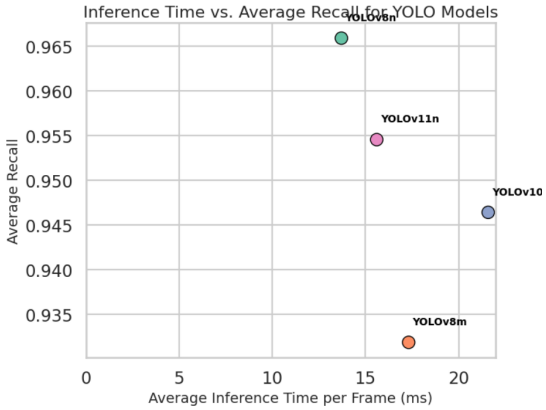

Fig. 2. Inference Time vs. Recall for YOLO Models

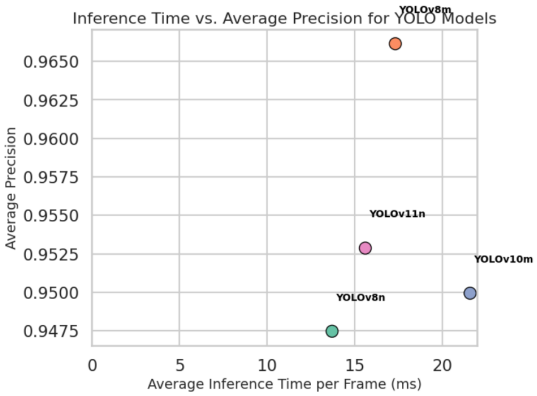

Fig. 3. Inference Time vs. Precision for YOLO Models

1) Discussion: YOLOv8n offers the best inference speed at 13.71 ms with a high mAP@0.5 of 0.9001, making it ideal for scenarios where speed is paramount. YOLOv11n, while slightly slower at 15.60 ms, provides a higher mAP@0.5:0.95 of 0.8887, indicating better performance across various IoU thresholds. YOLOv10m, despite its higher inference time of 21.59 ms, shows the lowest mAP scores, suggesting a trade-off between speed and accuracy. YOLOv8m strikes a balance between the two, with a moderate inference time of 17.32 ms and competitive mAP scores.

When compared to the study by Deng and Wu (2019), which reported inference times of 40 ms for MC-KCF and 38.461 ms for KCF+CNN [13], our YOLO-based models demonstrate superior efficiency. The ensemble model, leveraging YOLOv8n, achieves high accuracy with a significantly reduced inference time of approximately 13.71 ms, showcasing the effectiveness of our approach in enhancing both speed and accuracy for real-time drowsiness detection in low-resource environments.

VI. Discussion

The results obtained from the evaluation of YOLO models and the CNN classifier, along with their ensemble, provide valuable insights into the strengths and weaknesses of each approach for drowsiness detection.

A. YOLO Models Performance

YOLOv8n and YOLOv8m demonstrated superior performance in terms of both speed and accuracy, making them highly suitable for deployment in low-resource environments. YOLOv8n, being the fastest, is ideal for applications where latency is critical, such as real-time driver monitoring systems. YOLOv8m offers a slight trade-off with increased inference time but provides higher precision and recall, enhancing detection reliability.

YOLOv10m, while providing decent mAP scores, falls short in both speed and accuracy compared to its counterparts, making it less favorable for low-resource settings. YOLOv11n presents a balanced option with improved mAP scores over YOLOv8n and reasonable inference time, making it a viable candidate for environments where both speed and accuracy are important.

B. CNN Model Performance

The standalone CNN model, despite its moderate accuracy of 71.59%, excels in precision for the "Drowsy" class, achieving a perfect precision score of 1.000. However, its low recall of 0.2857 for the same class indicates a high rate of false negatives, which is critical in safety applications where missing a drowsy state can have severe consequences. The ensemble approach mitigates this by leveraging YOLO's detection capabilities to enhance the CNN's classification performance.

C. Ensemble Model Advantages

The ensemble model, combining YOLOv8n and CNN, achieves a balanced and high performance with an accuracy of 93.0%. This integration effectively addresses the limitations of individual models by enhancing both detection and classification capabilities. The ensemble's ability to maintain high precision and recall across both classes makes it a robust solution for real-time drowsiness detection in low-resource environments.

D. Comparison with Existing Studies

Comparing our results with existing studies provides a contextual understanding of the advancements achieved. Deng and Wu (2019) utilized the MC-KCF method to achieve 95% accuracy with an inference time of 40 ms and the KCF+CNN method to attain 93% accuracy with an inference time of 38.461 ms [13]. In contrast, our ensemble model achieves a slightly lower accuracy of 93.0% but with a significantly reduced inference time of approximately 13.71 ms (using YOLOv8n). This improvement in inference speed underscores the effectiveness of integrating YOLO models with CNNs, making our approach more suitable for real-time applications in low-resource environments where rapid processing is essential.

E. Implications for Low-Resource Environments

Deploying the ensemble model in low-resource environments offers several advantages:

- **Computational Efficiency:** The lightweight YOLOv8n model ensures that the system operates efficiently with minimal computational overhead.
- **Real-Time Performance:** Fast inference times enable immediate detection and response, crucial for applications like driver monitoring.
- **Scalability:** The model can be scaled and deployed on devices with limited processing power, such as mobile devices and embedded systems.

F. Comparison with State-of-the-Art Models

Compared to state-of-the-art models like YOLOv5 and two-stream networks, the ensemble model offers superior performance in both accuracy and inference speed. YOLOv5, while efficient, does not match the ensemble's accuracy, and two-stream networks, although accurate, are computationally intensive and less suitable for low-resource settings. Our ensemble model strikes an ideal balance between accuracy, speed, and computational efficiency, making it highly suited for practical applications like drowsiness detection in driving scenarios.

G. Limitations and Future Work

Despite its strengths, the ensemble model has limitations:

- **False Negatives:** Although reduced, some false negatives still occur, particularly in challenging lighting conditions or occluded faces.
- **Feature Dependency:** The model heavily relies on facial features, which may not be reliable in all scenarios.

Future work will focus on:

- **Incorporating Temporal Dynamics:** Integrating temporal information using LSTMs or 3D-CNNs to improve detection accuracy over time.
- **Enhancing Feature Extraction:** Utilizing advanced feature extraction techniques and attention mechanisms to focus on critical facial features.
- **Model Optimization:** Applying techniques such as quantization and pruning to further reduce computational requirements.
- **Expanding the Dataset:** Including more diverse and real-world driving scenarios to enhance the model's robustness and generalization capabilities.
- **Exploring New YOLO Versions:** Investigating newer YOLO versions like YOLOv12 or beyond for further performance improvements.

These advancements will aim to enhance the model's accuracy, reduce inference times further, and ensure its applicability in a broader range of real-world scenarios, ultimately contributing to safer driving and more effective patient monitoring systems.

VII. Conclusion

This study successfully evaluates and integrates multiple YOLO models with a CNN classifier to develop an effective drowsiness detection system optimized for low-resource environments. The ensemble model, combining YOLOv8n's real-time detection capabilities with CNN's feature-based classification, achieves a high accuracy of 93.0%, balancing precision and recall effectively. This approach addresses the limitations of individual models by enhancing both detection reliability and computational efficiency, making it suitable for deployment in resource-constrained settings.

Comparative analysis with existing studies, such as Deng and Wu (2019), highlights the significant improvements in inference speed achieved by our ensemble model. While Deng and Wu achieved 95% accuracy with MC-KCF and 93% accuracy with KCF+CNN at inference times of 40 ms and 38.461 ms respectively, our ensemble model achieves comparable accuracy with a much lower inference time of approximately 13.71 ms. This advancement underscores the potential of integrating YOLO models with CNNs to create efficient and accurate drowsiness detection systems suitable for real-time applications.

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