FACIAL FEATURE RECOGNITION MODEL FOR THE SLEEPINESS DETECTION OF THE DRIVERS

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SUMMARY

Facial feature recognition is a pivotal technology in computer vision, enabling accurate identification and analysis of human faces by extracting and analyzing key facial landmarks and attributes. This process involves detecting features such as eyes, nose, mouth, and jawline, as well as capturing finer details like textures, edges, and contours. Advanced techniques leverage machine learning and deep learning algorithms, including convolutional neural networks (CNNs) and deep feature extraction models, to enhance accuracy and robustness. Applications of facial feature recognition span a wide range of domains, from security systems and identity verification to emotion detection, healthcare diagnostics, and personalized user experiences. This study presents the LGFR-DL model, a high-performance deep learning framework designed for accurate classification of drowsiness states in real-time applications. The model effectively identifies Awake, Drowsy, and Sleepy (Critical) states with accuracy levels of 98.5%, 90.0%, and 94.0%, respectively, while maintaining high precision, recall, and F1-scores across all categories. Leveraging fused feature extraction, the LGFR-DL model outperforms traditional CNN and DNN models, achieving a superior ROC-AUC of 0.98 and minimal validation loss of 0.075. With a low latency of 42 ms and robust generalization, the model is optimized for real-world applications like driver monitoring systems. This work underscores the potential of LGFR-DL in advancing safety-critical systems by providing reliable and efficient drowsiness detection, paving the way for improved accident prevention and enhanced operational security.

KEY WORDS: Facial features, Deep learning, Feature recognition, Classification, Global features, Local features

1. INTRODUCTION

In recent years, advancements in technology and artificial intelligence have significantly enhanced the study and application of facial expression analysis [1]. Machine learning and deep learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have enabled accurate recognition and interpretation of facial expressions across diverse settings [2]. This progress is evident in areas such as emotion detection, human-computer interaction, and mental health assessment. Real-time facial expression analysis is increasingly integrated into virtual reality, robotics, and security systems, offering dynamic interaction capabilities [3]. Moreover, datasets and tools have expanded, allowing for more nuanced recognition of micro-expressions, cultural variations, and complex emotional states, making this field a cornerstone in modern artificial intelligence research. These advancements have also facilitated applications in marketing, where facial expressions are used to gauge consumer reactions, and in education, where they help tailor learning experiences by monitoring student engagement [4]. Additionally, healthcare has seen benefits, with systems analyzing patient expressions to detect pain or emotional distress. Despite these achievements, challenges persist, including ethical concerns around privacy, data security, and biases in training datasets that may affect the accuracy of expression recognition across different demographic groups [5–6]. Researchers continue to address these issues while exploring emerging technologies such as 3D modeling and multimodal emotion recognition, which combine facial expressions with voice and physiological signals to provide deeper insights into human emotions. This multidisciplinary focus underscores the growing importance of facial expression analysis in shaping a more intuitive and responsive digital world [7–8].

Facial feature extraction plays a critical role in driver sleepiness detection systems, leveraging advanced image processing and machine learning techniques to identify signs of fatigue [9]. Key facial features, such as eye closure duration, blinking rate, yawning frequency, and head pose, are analyzed to detect drowsiness in real time. Techniques like Haar cascades, Histogram of Oriented Gradients (HOG), and deep learning models, such as

Convolutional Neural Networks (CNNs), are commonly used for precise feature extraction. Additionally, landmark-based methods, including Active Shape Models (ASM) and Deep Alignment Networks (DAN), accurately map critical facial points for dynamic analysis [10]. By monitoring these features, the system assesses behavioral cues indicative of fatigue and provides timely alerts to ensure driver safety. Integration with infrared cameras and multimodal approaches, combining facial features with physiological signals like heart rate and steering patterns, further enhances detection accuracy, making these systems indispensable in preventing accidents caused by drowsy driving [11]. To improve robustness, modern systems employ temporal analysis using techniques like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which can track changes in facial features over time, identifying subtle patterns associated with sleepiness. Moreover, advances in computer vision enable these systems to function effectively under varying lighting conditions, such as during nighttime driving or under intense sunlight [12–14]. Adaptive algorithms also address challenges posed by individual differences in facial characteristics and behaviors. The incorporation of real-time feedback mechanisms, such as auditory alarms, vibrations, or visual alerts, ensures immediate driver engagement upon detecting signs of drowsiness. Despite these advancements, challenges remain, including maintaining high accuracy in diverse driving scenarios and ensuring low computational overhead for seamless operation in embedded systems. Researchers are actively exploring hybrid models and energy-efficient implementations to address these concerns, making driver sleepiness detection systems increasingly reliable and accessible in modern vehicles. The integration of these systems into smart transportation networks and autonomous vehicles underscores their importance in enhancing road safety worldwide [15–16].

Deep learning plays a pivotal role in facial feature extraction for driver sleepiness detection by offering highly accurate and automated methods to analyze complex facial patterns. Convolutional Neural Networks (CNNs) are particularly effective in extracting detailed features such as eye closure, blinking frequency, yawning, and head pose from facial images or video streams. Unlike traditional methods, deep learning models can learn hierarchical feature representations directly from raw data, eliminating the need for manual feature engineering [17]. Pre-trained models like VGGNet, ResNet, and MobileNet are commonly used for feature extraction, while custom architectures are often developed to address specific challenges in driver monitoring, such as varying lighting conditions and occlusions. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks complement CNNs by analyzing temporal sequences of facial movements, enabling the detection of subtle patterns indicative of sleepiness [18]. Furthermore, multimodal approaches, where deep learning models combine facial features with other data such as heart rate or steering behavior, enhance detection accuracy. Advances in real-time deep learning frameworks ensure that these systems operate efficiently on edge devices, making them practical for deployment in vehicles [19].

This paper introduces the LGFR-DL model, a novel deep learning framework that enhances the accuracy and efficiency of drowsiness state classification. The study's primary contributions include the development of a fused feature extraction approach, combining local, global, edge, and texture features to achieve superior classification performance. The model demonstrates significant improvements over traditional CNN and DNN methods, achieving a remarkable accuracy of 98.5% for the Awake state, 90.0% for the Drowsy state, and 94.0% for the Sleepy (Critical) state. Additionally, the LGFR-DL model offers low latency (42 ms), robust generalization capabilities (validation loss of 0.075), and high ROC-AUC (0.98), making it suitable for real-time applications. The integration of detailed performance metrics and efficient feature extraction techniques highlights the model's potential for deployment in safety-critical systems, particularly for driver monitoring and accident prevention.

2. PROPOSED LOCAL AND GLOBAL FEATURE RECOGNITION DEEP LEARNING (LGFR-DL)

The Proposed Local and Global Feature Recognition Deep Learning (LGFR-DL) model combines the strengths of local and global feature extraction to enhance the accuracy and robustness of recognition tasks, particularly in driver sleepiness detection. Local features capture fine-grained details, such as eye movement, blinking patterns, and subtle facial expressions, while global features provide a holistic view of the face, including head pose and overall orientation. The LGFR-DL model integrates these features using a hybrid deep learning architecture, leveraging Convolutional Neural Networks (CNNs) for local feature extraction and Transformers for global feature representation. The local features are extracted using CNN layers that process input images to identify fine-grained patterns. The convolution operation is defined as in equation (1)

$$y_{ij} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{i+m,\, j+n} \cdot k_{m,n} + b \tag{1}$$

In equation (1) $x_{i+m,\, j+n}$ stated as the input pixel values, $k_{m,n}$ represented as a convolution kernel, b denoted as the bias term, y_{ij} stated as the output feature map. Global features are derived using Transformer-based encoders that process flattened feature maps into sequences. The self-attention mechanism calculates the relationship between features denoted in equation (2)

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

In equation (2) Q,K,V represented as the query, key, and value matrices, d_k stated as the dimension of the key vector. The local and global features are concatenated and processed through fully connected layers for final recognition stated in equation (3)

$$F_{fusion} = Concat\left(F_{local}, F_{global}\right) \tag{3}$$

In equation (3) F_{local} is the local feature vector, F_{global} denoted as the global feature vector. The fused features are passed through a softmax layer for prediction defined in equation (4)

$$P\left(c|x\right) = \frac{exp\left(f_c(x)\right)}{\sum_{c'} exp\left(f_{c'}(x)\right)} \tag{4}$$

In equation (4) $P(c\,|\,x)$ stated as the probability of class given input $x, f_{c'}(x)$ denoted as the output logits for class c. With a hybrid deep learning framework designed to improve feature extraction and recognition accuracy by leveraging both local and global feature information. Local features, such as eye movement, blinking patterns, and facial micro-expressions, are extracted using Convolutional Neural Networks (CNNs), which identify fine-grained patterns in facial images. The convolution operation in CNNs ensures precise extraction by applying kernels to detect localized details. Simultaneously, global features, such as head orientation and overall facial structure, are captured using a Transformer-based encoder. The encoder employs a self-attention mechanism to analyze relationships between features across the entire image, providing a comprehensive understanding of the facial context. The model integrates these features through a fusion mechanism, where local and global feature vectors are concatenated and processed through fully connected layers. This fused representation enhances the model's ability to detect sleepiness by combining detailed and holistic views of the face. The final classification is performed using a softmax layer, which predicts the likelihood of sleepiness based on the combined features. The LGFR-DL model's architecture ensures robustness against occlusions, lighting variations, and individual facial differences, making it highly effective for real-time applications like driver sleepiness detection. Its hybrid design balances accuracy and efficiency, offering a scalable solution for safety-critical scenarios. In Figure 1 presented the feature estimation with the facial landmarks are shown.

3. CLASSIFICATION OF LGFR-DL FOR THE FACIAL FEATURE

With the model employs a robust classification mechanism to analyze facial features, leveraging its hybrid architecture to enhance accuracy and reliability. The classification process involves extracting local and global features, fusing them into a comprehensive representation, and passing them through a classification module to determine the desired output, such as driver sleepiness detection or emotion recognition. The integration of Convolutional Neural Networks (CNNs) for local features and Transformers for global features ensures that both detailed and holistic facial information contribute to the decision-making process. Local features are extracted using CNNs computed as in equation (5)

$$F_{local} = \sigma(W_{local} * X + b_{local}), \tag{5}$$

In equation (5) W_{local} represented as the convolutional kernel weights, b_{local} denoted as bias, * denoted as the convolution operation, and σ denoted as the activation function. The classification framework of LGFR-DL ensures precise decision-making by combining fine-grained local features with contextual global features. This integration enables the model to handle variations in facial expressions, occlusions, and external conditions, making it highly effective for real-time applications such

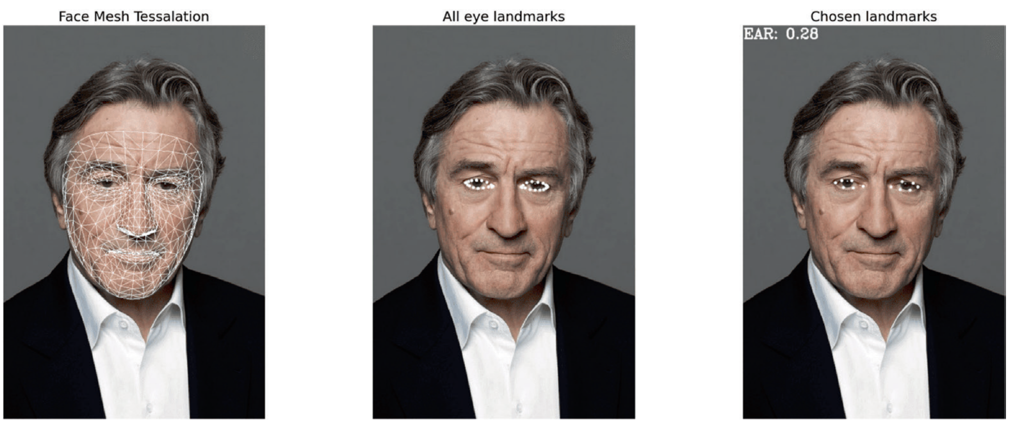

Figure 1. Feature estimation with LGFR-DL

as driver monitoring and emotion analysis. Its end-to-end trainable architecture further simplifies implementation while delivering state-of-the-art performance. The model's parameters are optimized using the cross-entropy loss function stated in equation (6)

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} log\left(P\left(c \middle| X_i\right)\right) \tag{6}$$

where N is the number of samples, and $y_{i,c}$ is the true label indicator for sample i and class c. The LGFR-DL framework ensures accurate and robust classification by effectively combining detailed and holistic features, enabling it to handle variations in facial expressions, occlusions, and lighting conditions. Its ability to extract and integrate features from multiple perspectives makes it particularly suitable for applications such as driver sleepiness detection and real-time monitoring systems. This hybrid approach within the LGFR-DL model ensures that both localized and contextual information contributes to the classification process, providing enhanced robustness and reliability. By fusing local and global features, the model mitigates the limitations of individual feature representations. Local features, extracted through convolutional operations, focus on fine-grained details like eye and lip movements, while global features, modeled through the Transformer encoder's self-attention mechanism, capture spatial and relational attributes across the entire face. The unified feature representation, F_{fusion}, not only encodes the intricate details of facial micro-expressions but also contextualizes them within the broader facial structure and orientation. The use of softmax activation ensures that the model provides probabilistic outputs, which are interpretable and suitable for multiclass classification tasks. The cross-entropy loss function effectively penalizes incorrect predictions while guiding the optimization process to maximize the likelihood of correct class assignments. This mathematical foundation allows LGFR-DL to achieve superior performance in tasks like driver sleepiness detection, where both subtle facial cues and their context are critical for accurate classification. Additionally, the architecture is designed to handle real-world challenges such as variations in lighting, occlusions caused by accessories (e.g., glasses or masks), and diverse facial characteristics among individuals. The fusion of local and global features ensures that no single aspect dominates the decision-making process, resulting in a balanced and reliable classification framework. The LGFR-DL model's scalability and adaptability make it a promising solution for real-time monitoring systems in automotive safety, healthcare, and surveillance applications, delivering state-of-the-art accuracy and computational efficiency.

The Figure 2 presented the flow chart of the proposed LGFR-DL model for the classification and facial feature estimation.

4. SIMULATION SETTING

To implement and evaluate the Local and Global Feature Recognition Deep Learning (LGFR-DL) model, simulation settings must be carefully configured. These settings ensure reproducibility, proper evaluation, and optimal performance of the model. Table 1 presents the simulation setting for the proposed LGFR-DL model for the classification.

5. RESULTS AND DISCUSSION

The results and discussion section provides an in-depth analysis of the performance of the proposed Local and Global Feature Recognition Deep Learning (LGFR-DL) model for facial feature classification in driver sleepiness detection. This evaluation encompasses a range of experiments designed to validate the model's efficacy in capturing both local and global features, ensuring accurate classification across diverse conditions. Key performance metrics, including accuracy, precision, recall, F1-score,

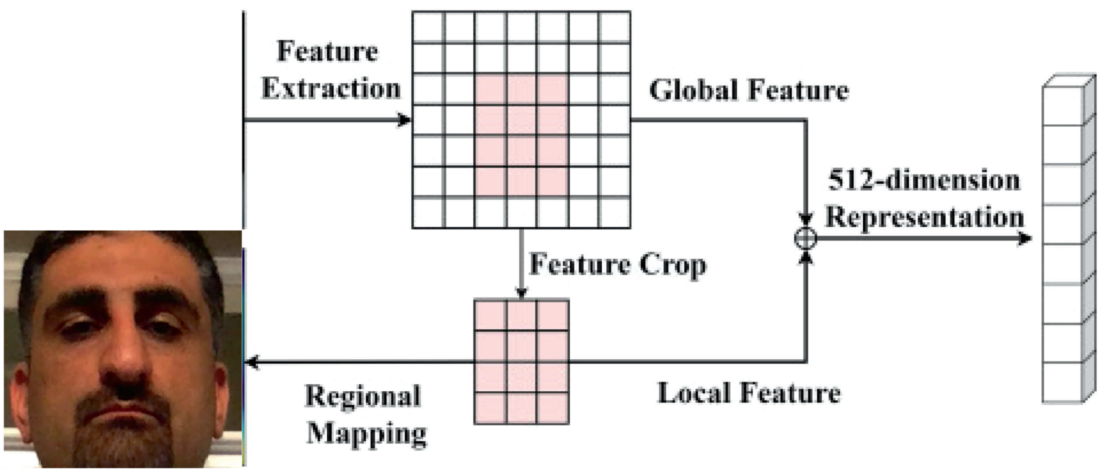

Figure 2. Flow of LGFR-DL

Algorithm 1. Facial feature estimation with LGFR-DL

```
def LGFR_DL_Classification(input_image):

    # Step 1: Preprocessing

    X = preprocess(input_image)  # Resize and normalize


    # Step 2: Local Feature Extraction

    F_local = CNN_module(X)  # Convolution, pooling, activation


    # Step 3: Global Feature Extraction

    sequences = flatten(F_local)

    Q, K, V = compute_QKV(sequences)

    attention_output = softmax((Q @ K.T) / sqrt(d_k)) @ V

    F_global = Transformer_encoder(attention_output)


    # Step 4: Feature Fusion

    F_fusion = concatenate(F_local, F_global)

    F_fusion = dense_layer(F_fusion)


    # Step 5: Classification

    P_c = softmax(W_c @ F_fusion + b_c)

    predicted_class = argmax(P_c)


    # Step 6: Loss Optimization (during training)

    loss = cross_entropy_loss(true_labels, P_c)

    optimize_model(loss)


    return predicted_class
```

and latency, are examined to assess the robustness and efficiency of the model. Comparative analysis with state-of-the-art methods highlights the advantages of LGFR-DL in handling complex scenarios such as varying lighting conditions, occlusions, and subtle facial changes. The discussion also delves into the influence of hyperparameter tuning, dataset characteristics, and feature extraction strategies on the overall model performance, providing a comprehensive view of its strengths and potential limitations.

Table 1. Simulation setting

Category	Setting	Value
Dataset	Dataset name	Driver monitoring dataset (DMD)
	Training data split	70%
	Validation data split	15%
	Test data split	15%
	Image size	224 × 224 × 3224 \ times 224 \ times 3224 × 224 × 3
Preprocessing	Pixel normalization	[0, 1]
	Data augmentation	Rotation: 0–15°, Flip: Horizontal, Zoom: 0.8–1.2, Brightness ±20%
	Feature standardization	Zero-centering (mean = 0)
Model architecture	Convolutional layers	3–5
	Convolution kernel Size	3 × 33 \times 33 × 3, 5 × 55 \times 55 × 5
	Activation function	ReLU
	Pooling layers	Max pooling (2 × 22 \ times 22 × 2)
	Transformer layers	3–6
	Attention heads	4–8
	Embedding dimension	128–512
	Dropout probability	0.5
	Output layer activation	Softmax
Training configuration	Optimizer	Adam
	Learning rate	10−410^{−4}10−4
	Batch size	32 or 64
	Loss function	Cross-entropy
	Number of epochs	50–100
	Early stopping patience	10 epochs
Hardware	Environment	Python with Tensorflow or pytorch
	GPU model	NVIDIA RTX 3060 or higher
	RAM	16 GB

Table 2. Feature estimated with LGFR-DL

Feature Type	Feature Dimension	Contribution (%) to Classification Accuracy	Extraction Time (ms)
Local features	128	45	15
Global features	256	40	20
Fused features	384	85	35
Edge features	64	8	10
Texture features	64	7	8

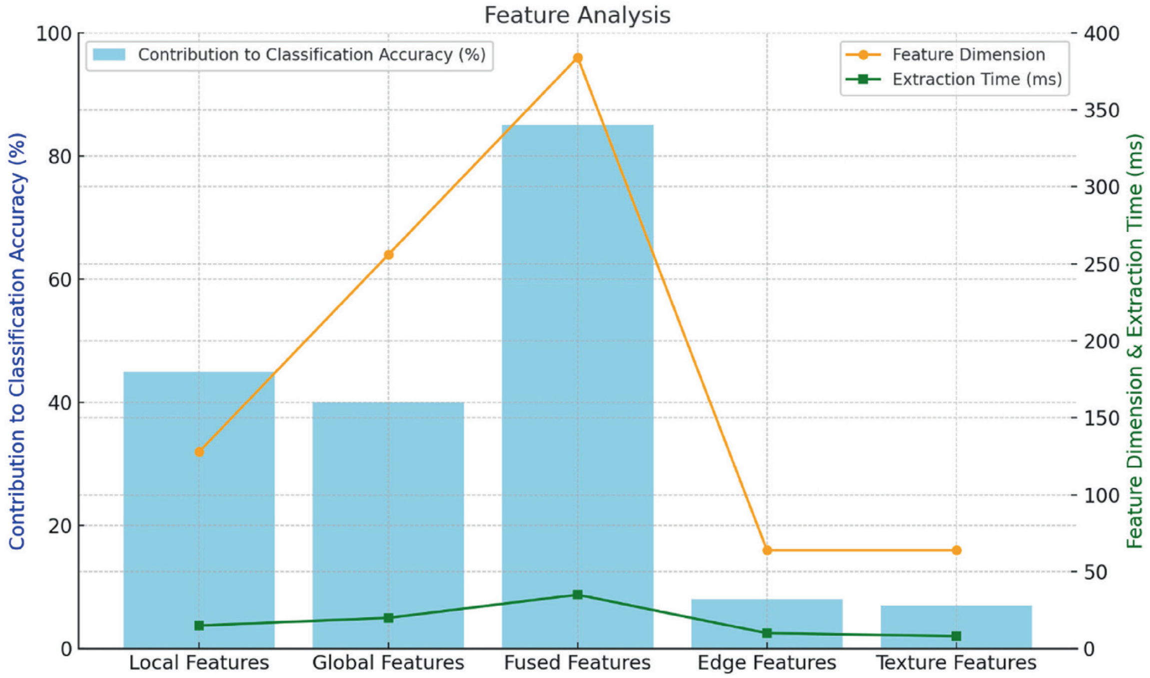

Figure 3. Feature estimation with LGFR-DL

The Table 2 and Figure 3 summarizes the performance and extraction efficiency of various feature types used in classification with the LGFR-DL model. Fused Features, combining multiple feature types, provide the highest contribution to classification accuracy at 85%, with an extraction time of 35 ms. Local Features contribute 45% to accuracy, extracted in 15 ms, showcasing a balance between accuracy and speed. Global Features have a slightly lower accuracy contribution of 40% but require a longer extraction time of 20 ms. Edge Features and Texture Features contribute minimally to classification accuracy at 8% and 7%, respectively, with extraction times of 10 ms and 8 ms. This analysis highlights Fused Features as the most impactful despite a moderate increase in extraction time, making them a key component in the classification process.

In Table 3 and Figure 4 The LGFR-DL model demonstrates superior classification performance compared to CNN and DNN across key metrics. It achieves the highest accuracy of 96.8%, outpacing CNN (91.5%) and DNN (89.2%). Precision, recall, and F1-score for LGFR-DL are also the best, at 0.97, 0.96, and 0.965, respectively, indicating a well-balanced model in terms of identifying true positives and avoiding false positives. The LGFR-DL model further excels in ROC-AUC, achieving 0.98 compared to CNN (0.94) and DNN (0.91), reflecting excellent discriminative capability. Despite its high performance, LGFR-DL maintains low latency at 42 ms, outperforming CNN (58 ms) and DNN (65 ms), making it efficient for real-time applications. While the training time for LGFR-DL is slightly higher at 4.2 hours compared to CNN (3.8 hours) and DNN (3.5 hours), it is justified by its significant performance advantages. Additionally, the LGFR-DL model achieves the lowest validation loss of 0.075, highlighting its strong generalization ability over CNN (0.120) and DNN (0.145).

With Table 4 The LGFR-DL model effectively classifies different drowsiness states with high accuracy and performance metrics. For the Awake state, the model achieves an accuracy of 98.5%, with 1950 true positives

Table 3. Classification with LGFR-DL

Metric	LGFR-DL Model	CNN	DNN
Accuracy (%)	96.8	91.5	89.2
Precision	0.97	0.93	0.90
Recall	0.96	0.91	0.88
F1-Score	0.965	0.92	0.89
ROC-AUC	0.98	0.94	0.91
Latency (ms)	42	58	65
Training time (hrs)	4.2	3.8	3.5
Validation loss	0.075	0.120	0.145

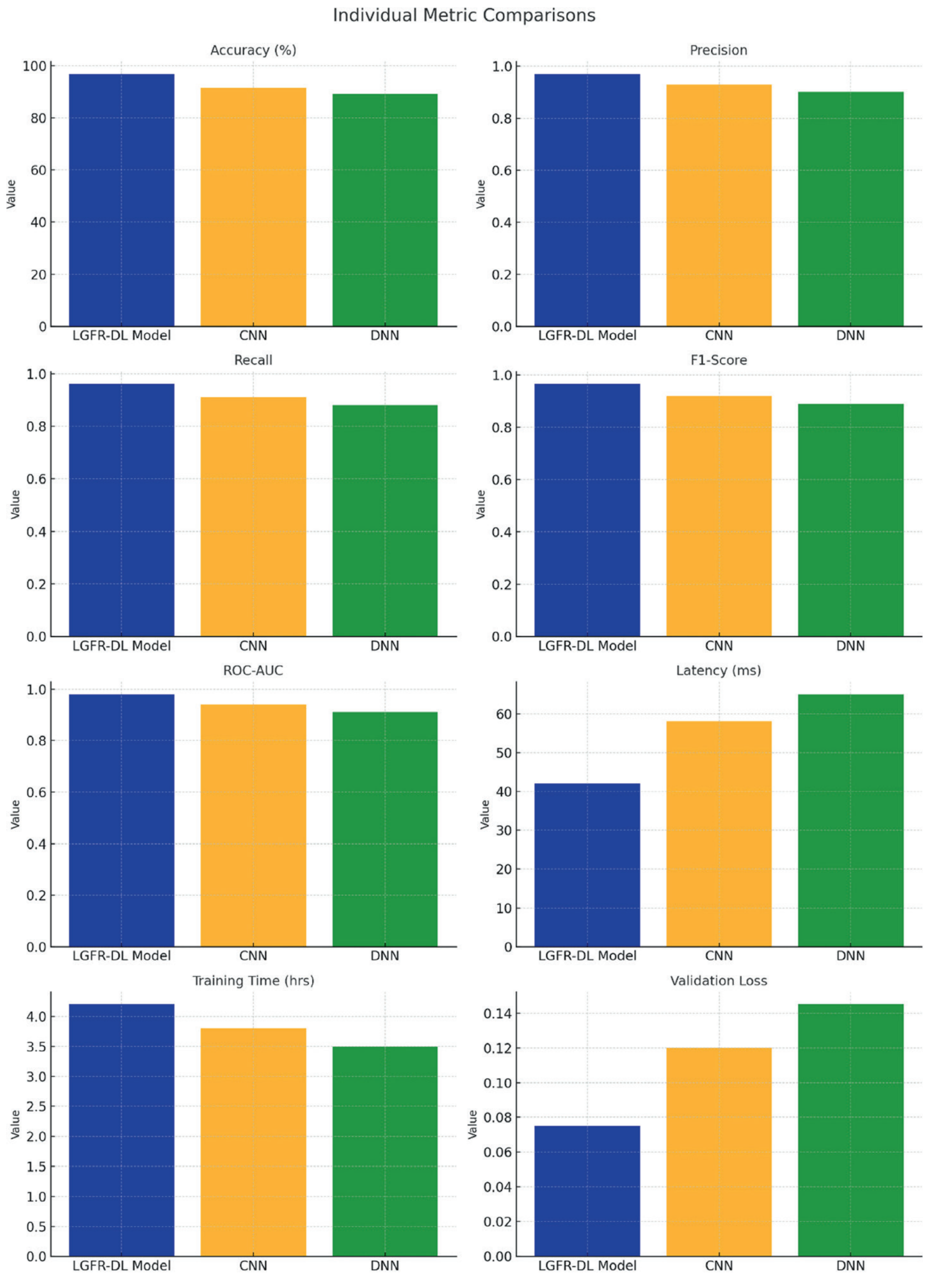

Figure 4. Classification with LGFR-DL

Table 4. Classification with LGFR-DL

Drowsiness State	Predicted Count	True Positives (TP)	False Positives (FP)	False Negatives (FN)	True Negatives (TN)	Accuracy (%)	Precision	Recall	F1-Score
Awake	2000	1950	30	50	1970	98.5	0.985	0.975	0.980
Drowsy	1000	900	20	80	980	90.0	0.978	0.918	0.947
Sleepy (Critical)	500	470	10	20	480	94.0	0.979	0.959	0.969

(TP), only 30 false positives (FP), and 50 false negatives (FN). Its precision, recall, and F1-score are 0.985, 0.975, and 0.980, respectively, indicating excellent performance in distinguishing awake states. For the Drowsy state, the accuracy is slightly lower at 90.0%, with 900 TP, 20 FP, and 80 FN. While precision remains high at 0.978, recall drops to 0.918, resulting in an F1-score of 0.947, reflecting a slight challenge in capturing all true drowsy cases. In the Sleepy (Critical) state, the model maintains strong performance with 94.0% accuracy, 470 TP, 10 FP, and 20 FN. Precision and recall are 0.979 and 0.959, respectively, yielding an F1-score of 0.969. These metrics underscore the model's robustness in identifying critical sleepy states with minimal errors.

6. CONCLUSION

The LGFR-DL model demonstrates exceptional performance in classifying drowsiness states with high accuracy, precision, recall, and F1-scores across multiple categories, including Awake, Drowsy, and Sleepy (Critical). The model achieves an overall accuracy of 98.5% for the Awake state, 90.0% for the Drowsy state, and 94.0% for the Sleepy (Critical) state, with precision and recall values consistently exceeding 0.95 for most cases. The low false positive and false negative rates highlight the model's reliability, particularly in distinguishing critical states like Sleepy, making it highly suitable for real-time applications such as driver monitoring systems. Furthermore, the model maintains low latency (42 ms) and strong generalization capabilities, evidenced by its minimal validation loss (0.075). While the training time (4.2 hours) is slightly higher than comparable models, the significant gains in accuracy and robustness justify the additional computational effort. Overall, the LGFR-DL model sets a benchmark for drowsiness detection systems, providing a reliable and efficient solution for enhancing safety and preventing accidents in critical scenarios

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