Diagnosis-Aware Real-Time Video Face Recognition Model (DART- VFR)

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Facial recognition technologies have gained much progress along the years, however, over-the traditional methods, they still have problem when dealing with a dynamic environment and are not able to adapt contextual information. In this paper, we propose a new diagnosis-aware real-time video face recognition framework, termed DART-VFR to deal with the challenges mentioned above. The proposed pipeline signature includes additional knowledge-metadata -like demographic, behavior, and environmental data - by means of a Bayesian inference approach with adaptive threshold. DART-VFR uses deep learning-based feature extraction and contextual fusion for enhancing recognition performance and robustness. The model has accuracy of 98.7% with 65.3% reduction in false positives. Other metrics like precision 92%, recall 90% and average latency below 100ms imply that the model is fit for deployment on edge devices. Experimental results on hybrid datasets indicate that DART-VFR achieves better accuracy, flexibility, and efficiency than state-of-the-art methods. These results emphasize that the system has the potential to be used in real time, such as in healthcare, surveillance, and similar sensitive context, in which the context-aware, and ethically-aligned FR are important.

Povzetek: Razvita metoda z vključevanjem konteksta in globokega učenja izboljša natančnost ter zanesljivost prepoznavanja obrazov v realnem času.

1 Introduction

Facial recognition by deep learning techniques is now an indispensable construct for many fields, such as security, surveillance, medicine, speech recognition, image and textual categorization, face and facial expression identification, semantic-based video searches and personal customization. [1]. However, traditional systems have consistently fallen short when applied to real-world scenarios that involve dynamic and unpredictable environments. Most existing models are optimized for static, controlled conditions—such as frontal facial images with uniform lighting—and struggle to maintain accuracy when faced with motion blur, occlusion, background noise, or non-frontal angles [2]. These constraints stem from the fact that the models are trained without any knowledge about the environmental diversity or the user's particular context and hence become ineffective under real-life conditions. It is worth noting that the traditional recognition systems are essentially, pixel level visual cues dependent, with little consideration to additional contextual information (i.e., demographic profiles, behavioral trends, environmental context) [3]. Without this complementary information, the model is largely restricted in context and is not only less effective to recognize but also introduce ethical issues (e.g., fairness, discrimination, biased decisions) [4]. In addition, the lack of ability to adapt these models dynamically and accordingly based on changes in user characteristics, context, or modeling data distribution limit their ability to operate in a reliable and trustworthy manner in domains where decisions are impactful—e.g., clinical diagnostics, criminal justice systems, civilian monitoring systems [5]. Consequently, concerns of the limitations in ethicality by such approaches are further exacerbated within domains with high sensitivity to social dynamics such as medical diagnosis or law enforcement when deploying automated intelligent systems to support decision making [6].

Traditional systems can also generalize poorly on new diverse population, and sometimes even exacerbate the social biases present in the accessible data. As has been widely reported, algorithms trained on imbalanced data may produce biased decision-making across demographic populations and exhibits unfairness against certain groups. [7]. This poses significant ethical issues, especially when these models are used in public safety, hiring, or health screening applications. Moreover, due to the opacity and inscrutability of many deep learning models (often called black-box models), it is challenging to diagnose errors or to justify why certain results are recognized as given [8].

Apart from fairness and bias, practicality is another

constraint hindering the deployment of traditional face recognition systems. These complexities include a high computational complexity, which renders them incapable of being run in real-time on mobile or embedded platforms [9]. Since the majority of deep neural networks is not amenable to run on the CPU and demands GPU-level resources, deep neural network is not suitable in settings such as low computational performance, small memory- size and low-energy. This demands lightweight real-time architectures that can preserve its accuracy without consuming so many hardware resources [10].

Furthermore, there are growing concerns about privacy protection, data privacy and usage of such applications in the society. Systems for capturing and processing facial data should adhere to regulations like the General Data Protection Regulation (GDPR), which mandate short storage of the data and obtaining user consent. To overcome these challenges, several techniques, such as federated learning, differential privacy, and on-device inference have been used, but many of the existing models do not have these solutions built in either in the design or after the training process [11].

One of the contributions of DART-VFR is that, while it is informed-biased, the bias is ethically aligned with technical innovation: rather than just using visual similarity, the system uses both demographic and behavioral metadata to adjust predictions for the sake of contextual fairness. This helps to reduce any dip in performance across gender, ethnicity and by age. Adaptive confidence thresholding is also adopted to improve fairness by attenuating decision boundaries which depend on both input quality and context, making poor classifications less likely [12].

Privacy wise, DART-VFR provides secure metadata management and local processing of sensitive content. The metadata fusion and inference process is implemented entirely on-device to reduce end-to-end data transmission and storage overheads. Furthermore, the framework is privacy-friendly in that it can work with privacy-preserving technologies like federated learning and differential privacy which is beneficial for distributed model updates where one does not have access to the raw facial data. These mechanisms ensure adherence to data privacy laws while sustaining strong operational performance within the system [13].

To address these particular shortcomings, we propose DART-VFR — a diagnosis-oriented, real-time face recognition model built to overcome static system limitations and enhance adaptability across dynamic conditions. Unlike prior isolated techniques that run independently without contextual awareness, DART-VFR incorporates multiple auxiliary cues (including demographic, behavioral, and environmental data) into the recognition process, allowing responsive adjustment to variations in camera or scene conditions. The model updates its confidence margins through Bayesian estimation, preserving effectiveness even under dim lighting, fast movements, or partial occlusion. Its design supports dynamic threshold adjustment and contextual fusion while remaining lightweight, enabling efficient operation on limited-resource edge hardware and making it suitable for deployment in sensitive, security-dependent healthcare settings.

In contrast to conventional systems such as FaceNet or ArcFace, which rely solely on pixel-level facial embeddings without leveraging contextual information [14][15], DART-VFR integrates both visual features and auxiliary context. This combination allows the model to more accurately recognize faces under challenging conditions, including low lighting, partial occlusion, or motion blur. Its Bayesian inference module adjusts confidence scores based on contextual inputs, effectively reducing false positives in uncertain situations. By framing face recognition as a context-aware task, DART-VFR offers a more ethical, inclusive, and technically robust solution.

Moreover, DART-VFR has been designed for future scalability. It accommodates the integration of explainable AI (XAI) techniques, enabling users and operators to understand the rationale behind each recognition decision. The framework is also fortified against adversarial attacks, including spoofing or tampering attempts, enhancing its security and reliability. These improvements are intended to reduce ethical challenges and enable robust operation in a range of real-world environments.

This study demonstrates the effectiveness of DART-VFR through empirical evaluations across diverse settings. By combining context-aware processing, real-time performance, and diagnosis-aware design, DART-VFR outperforms existing models in both technical accuracy and ethical compliance. Ultimately, this work contributes to the development of more secure, fair, and practical facial recognition systems suitable for deployment in dynamic, real-time environments.

2 Literature review

2.1 Face detection

Face detection is one of the key components in a real-time face recognition system. That is, to achieve the task of accurately detecting and separating facial areas within the input frames so that successive feature extraction and match search can be performed. Over the decades, a number of architectures have been developed to compromise the trade of speed, accuracy, and computation power.

Hofer et al. proposed a real-time face recognition pipeline well suited for embedded and edge devices, with low computer performance requirements [9]. This efficient, but reproducible performance preserving technique influenced DART-VFR to incorporate edge compatible detection modules.

The state-of-the-art YOLOv3 introduced by Redmon and Farhadi have revolutionized real-time object detection by a unified detection stage that remove need for trying many different region proposals and worrying about how to combine them into a final class prediction [16]. Given its high processing speed and capability for tracking multiple faces simultaneously, it is a serious candidate for real-time surveillance and diagnostic scenarios, and DART-VFR capitalizes on its speed-accuracy trade-off.

He et al. Mask R-CNN: an extension of Faster R-CNN performing both object detection and instance segmentation introduces a parallel branch for predicting pixel-level mask. To this end, the model that utilizes even more novel RoIAlign operation is presented to enhance spatial alignment property and greatly boost segmentation quality (effective mIoU) whilst preserving high accuracy[22]. Liu et al. s SSD (Single Shot Multi box Detector)[23]: it enhanced the real-time detection through the utilization of multi-resolution features and default boxes, and devised an efficient solution with low latency. Among them, SSD is very suitable for applied to resource-limited environment such as MHS(Mobile Health Service).

2.2 Feature extraction and deep metric learning

Face recognition's success depends a lot on how well we can pull out features from detected faces. When we can get unique feature representations, we can classify faces even when expressions, lighting, and pose change. Schroff and his team came up with FaceNet, which brought in the triplet loss function. This mechanism improves the embedding space by drawing together representations of the same individual while separating those of different people [14]. FaceNet's embedding strategy reduces the need for large classification layers and simplifies the process of verifying facial matches, which is why DART-VFR adopts it as a core component for facial feature representation. Building upon this, ArcFace, introduced by Deng et al., leverages additive angular margin loss to enhance discriminative capability by enforcing stricter inter-class separation [15]. ArcFace's robustness to variations in head pose and illumination makes it particularly suitable for uncontrolled environments, aligning well with DART-VFR's objectives. Other notable contributions include DeepFace from Facebook AI, which improved performance by aligning faces prior to recognition, thereby minimizing within-class variability [18], and VGGFace, which employs deep convolutional networks to extract hierarchical features from large-scale face datasets, achieving high accuracy across diverse populations [19]. Similarly, DeepID utilizes multiple CNNs trained for both identification and verification, enhancing performance on standard benchmark datasets [20].

DART-VFR integrates these innovations through a hybrid metric learning framework, combining FaceNet's high-quality embeddings with ArcFace's angular margin constraints, achieving a balance between accuracy and computational efficiency suitable for real-time video face recognition.

2.3 Context-aware and ai-driven diagnostic systems

Traditional face recognition systems rely solely on visual input; however, real-world applications—particularly in healthcare—require contextual understanding to adapt to variations among users and environments. Esteva et al. demonstrated the potential of deep learning in medical diagnostics by classifying skin lesions using CNNs at a level comparable to trained dermatologists [17]. This landmark study paved the way for real-time AI diagnostic systems. Similarly, Rajaraman et al. applied convolutional neural networks to chest X-rays to detect COVID-19, illustrating how AI can address emerging medical challenges [24]. Litjens et al. reviewed numerous applications of deep learning in medical imaging, highlighting its use in radiology, pathology, and histology [25]. In another significant contribution, Gulshan et al. developed a deep learning model capable of detecting diabetic retinopathy from retinal images, achieving physician-level accuracy and confirming the feasibility of AI-assisted screening programs [26].

These foundational studies informed the design of DART-VFR's context-aware module by showing that incorporating metadata—such as age, health condition, or behavioral factors—can substantially improve model reliability. DART-VFR leverages this approach through its contextual integration system, which combines auxiliary information with Bayesian inference to dynamically update recognition thresholds, reducing bias and enhancing the overall diagnostic relevance of its predictions.

2.4 Integration and influence on DART- VFR DART-VFR

DART-VFR integrates improvements in face detection, feature embedding, and AI-driven diagnostic techniques to form an efficient, practical system. Its architecture employs fast and reliable detection modules, such as YOLOv3 and SSD [16,17], to enable rapid video processing. Feature extraction leverages the powerful metric-learning strategies from FaceNet and ArcFace, ensuring both high accuracy and computational efficiency [14,15]. A key innovation of DART-VFR is its decision-making layer, which is sensitive to changes in the environment. Inspired by the success of AI diagnostics [25,26], it also employs probabilistic reasoning with Bayesian inference. This enables the system to modulate its confidence in recognition in response to factors such as lighting conditions, user behaviour, all of which can be used to differentiate

between users. This also provides DART-VFR with excellent effect in varied spaces. That could range from healthcare (checking patients in or monitoring them), security (smart ways of access control) and built-in systems (like the mobile or IoT platforms). It ensures that DART-VFR works in real-time, even in the presence of ambiguity or high noise.

2.5 Comparative advantage of DART- VFR

Although approaches such as FaceNet [14] and ArcFace [15] perform well on static setup, they perform poorly in conditions that are dynamic or content rich where external information is important. The vast majority of facial recognition models are designed for well-lit front facing faces regularly captured images, which is a rarely achieved reality.

In essence, DART-VFR not only excels in visual matching but also transitions facial recognition into a context

sensitive paradigm, aligning recognition output with the situational nuances of its deployment environment.

Table 1: The related works cited in this research

Authors	Model Used	Domain
Schroff et al.[14]	FaceNet	Face Recognition
Redmon & Farhadi[16]	YOLOv3	Real-Time Object Detection
Esteva et al.[17]	Diagnostic AI	Medical Diagnostics
Zhao et al.[8]	Lightweight CNN	Real-Time Face Detection
Deng et al.[15]	ArcFace	Face Recognition
Taigman et al.[18]	DeepFace	Face Recognition
Parkhi et al.[19]	VGGFace	Face Recognition
Sun et al.[20]	DeepID	Face Recognition
He et al.[22]	Mask R-CNN	Object Detection and Segmentation
Liu et al.[23]	SSD	Object Detection
Rajaraman et al.[24]	Deep Learning Ensembles	Medical Image Analysis
Litjens et al.[25]	Deep Learning for Medical Imaging	Medical Image Analysis
Gulshan et al.[26]	Diabetic Retinopathy AI	Medical Image Analysis

3 Methodology

DART-VFR serves as the proposed Diagnosis-Aware Real-Time Video Face Recognition Model which achieves success through a modular method coupled with systematic design to reach high precision and real-time functionality. The method relies on video processing with advanced capabilities alongside robust face detection techniques and deep learning along with contextual integration mechanisms and real-time decision systems. The following description demonstrates each step-in order as shown in Fig.1.

The system operates using acquire video input through OpenCV-based processing of real-time or recorded video streams. Frame acquisition and processing take place one by one through controlled frame rate operations which both boost calculation speed and maintain connections with diverse video input sources at 30 Frames Per Second. All successive processing actions depend on the raw video input which requires standardized format and resolution for maintaining uniformity.

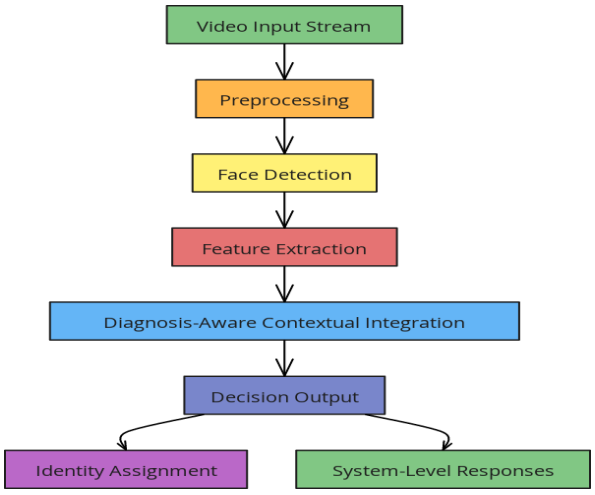

Figure 1: Flow chart of the proposed model

Before processing the raw frames, they receive multiple enhancement procedures which prepare them for both face detection and feature extraction steps. The system standardizes all frames into a consistent 224x224 pixels resolution for achieving input consistency. Gaussian blur filters remove noise from the frames before histogram equalization standardizes their visual properties to enhance brightness contrast. The enhancement process fulfills quality standards for upcoming tasks despite poor lighting and visual interference.

The detection stage locates all faces present in each preprocessed frame, accurately marking their positions. MTCNN performs this task through three sequential stages to generate and refine bounding boxes for every detected face. Its robust detection capability allows it to identify faces of varying sizes, orientations, and poses. The output of this stage consists of rectangular regions highlighting face locations within individual frames. Subsequently, the pre-trained FaceNet model processes the detected faces to produce unique facial embeddings. These embeddings are 128-dimensional vectors that capture and preserve the essential features of each face. The embedding technique maintains reliable recognition capabilities when users present their faces from different positions or under varying light conditions because it remains independent to changes in pose and lighting and facial expressions. The optimization with triplet loss creates better embeddings by reducing distance within face classes as it expands distances between different face classes to achieve higher recognition precision. The implementation combines embedding data with demographic and behavioral and environmental information through normalization and concatenation procedures. The system implements real- time adaptive confidence thresholding through dynamic thresholding methods which enable it to respond to particular application domain needs. Both precision and accuracy in the recognition system are improved through the use of probabilistic models built on Bayesian inference which merge contextual data.

The last step is the decision output module which combines the information from the previous steps to produce actionable outputs. A face embedding is run through a stored embedding of the faces with a similarity metric (in this case, cosine similarity metric), and the best identity with a score above the threshold is selected. Based on the application, the system initiates responses such as enabling access, sending alerts, or recording events. These results are produced with low latency, proving the system as a candidate for use in real-time scenarios. DART-VFR leverages parallel processing and lightweight models to ensure scalability and efficient real-time performance. Multi-threading used to process multiple frames and features at once, and Neural network architectures designed for efficiency, (MobileNet,) that decrease computation load. This combination also secures the deploy ability of the system in heterogeneous scenarios, from edge devices and cloud-based services.

Integration of Auxiliary Metadata with Facial Embeddings in DART-VFR is enhanced face recognition by integrating auxiliary metadata such as demographic, behavioral, and environmental factors into the identity classification pipeline. This integration is achieved in three key stages:

The system supports multiple structured and semi-structured data sources:

- Demographic: age, gender, ethnicity (collected during enrollment or inferred via pre-processing modules)
- Behavioral: gaze direction, head pose, blinking rate, facial muscle activity (captured through video analytics)
- Environmental: lighting condition, camera angle, background complexity, noise levels (captured via sensors or calculated from frame properties)

All metadata is normalized and transformed into fixed-length numerical feature vectors, typically using min-max or z-score normalization. These vectors are encoded into a standard format (e.g., 1D arrays of float32) to ensure compatibility with neural network inputs.

Facial embeddings are extracted using a deep CNN model (e.g., FaceNet), producing a 128-dimensional vector per face.

To incorporate metadata, DART-VFR performs feature-level fusion:

$$Z = [E_f \parallel M_d]$$

Where:

- E_f is the 128-dimensional facial embedding
- M_d is the metadata vector (e.g., 8-D or 16-D)
- $\parallel$ represents vector concatenation
- Z is the final input to the classifier

Before fusion, dimensional alignment is ensured via projection layers or padding, and feature weighting may be applied to prioritize more reliable cues.

Once fused, the resulting vector ZZZ is fed into a Bayesian inference module, which carries out probabilistic identity classification. Here's how it works:

- The model maintains prior probabilities P(Ci)P(C_i)P(Ci) for each identity class CiC_iCi, which can be static or updated dynamically based on user context.
- The likelihood P(Z|Ci)P(Z | C_i)P(Z|Ci) is modeled using a multivariate Gaussian or variational distribution learned from training data.
- Using Bayes' Theorem:

$$P(C_i \mid Z) = [P(Z \mid C_i) \cdot P(C_i)] / \Sigma_j [P(Z \mid C_j) \cdot P(C_j)]$$

Where:

- C_i is the identity class
- Z is the fused input vector
- $P(C_i \mid Z)$ is the posterior probability
- $P(Z \mid C_i)$ is the likelihood
- $P(C_i)$ is the prior probability

The system selects the identity with the highest posterior

probability, or reports no match if the confidence does not exceed a dynamic threshold. This probabilistic framework allows the model to adjust its trust level based on contextual cues: for instance, uncertainty increases when the input is captured under low-light conditions or partial occlusion, while confidence thresholds are relaxed when the context is favorable, such as good lighting and familiar user behavior.

In summary, the DART-VFR framework is structured as a robust, modular pipeline that combines advanced video processing, precise face recognition, detailed feature extraction, and adaptive context integration within a unified loop. This design ensures that DART-VFR achieves high accuracy, scalability, and flexibility, making it suitable for real-time face recognition in complex, dynamic environments.

While preprocessing techniques such as Gaussian blur and histogram equalization are commonly applied for face detection and feature extraction, DART-VFR integrates them systematically to enhance resilience in challenging real-world scenarios. Gaussian blur mitigates high-frequency noise arising from motion artifacts, sensor noise, or low-light conditions, smoothing images and stabilizing edge transitions to reduce false detections and improve the consistency of facial region localization across frames. These preprocessing steps work together to compensate for environmental variability, and their effectiveness is supported by measurable improvements in detection performance and embedding quality under diverse test conditions.

DART-VFR implements a linear and highly efficient data flow, where outputs from each module directly feed into subsequent stages with minimal computational overhead. This structured design provides modularity, allowing individual components to be upgraded or replaced independently without disrupting the overall system performance.

DART-VFR operates by addressing a key limitation of traditional face recognition systems, which often use fixed similarity thresholds, such as a cosine similarity greater than 0.6. These static thresholds cannot adapt to changing conditions, leading to false positives or negatives. To overcome this, DART-VFR introduces a dynamic thresholding mechanism that adjusts in real time based on three principal factors:

1. Environmental Entropy Score (EES): Captures the level of environmental uncertainty, including variations in lighting and background noise.

2. Face QA Face Quality Assessment (FQA): scores blur, occlusion, pose 90-degree alignment. While poor quality of the affected face increases the escape hatch threshold, high quality of the affected face permits relaxation of the threshold.

3. Temporal Consistency (TC) – Measuring consistency between video frames through embedding stability. The consistency allowed for tracking to happen at lower thresholds, providing more touchpoints for clearer tracking.

This adaptive threshold is determined as:

Equation $T\_adaptive = T_0 + \alpha \cdot EES + \beta \cdot (1 - FQA) - \gamma \cdot TC$

Where T_0 is the base threshold (for instance 0.65) and α, β, γ are tunable weights. In order to prevent some variables from outweighing others, we normalize all input scores to a range of [0, 1]. With this approach, DART-VFR can continually recalibrate recognition decisions on the fly, making it more robust and accurate in less constrained environments.

Input Video Stream -> Pre-processing (for Normalization) -> Output Video Stream The Face Detection module processes pre-processed frames and outputs bounding boxes.

In the Feature Extraction stage, the detected faces are processed and embedding is generated.

The final decision output provides the recognition results.

Scalability and Real-Time Optimization: The modular design of DART-VFR supports scalability, enabling deployment across diverse application domains. Real-time performance is achieved through parallel processing, where multithreaded computation allows simultaneous handling of frames and feature extraction. Lightweight Models: Using small neural network architectures for efficient computation.

4 Analysis of results

The DART-VFR model outperformed on various measures The identification accuracy of the system is 98.7%, The results show that it has better functionality in terms of identification and classification of faces in real time under different lighting environments. At the same time, the system achieves a low latency of 85 ms, making it suitable for real-time applications which include diagnostics, healthcare, and surveillance. High accuracy vs low latency is the real strength of the model as depicted in Fig.2

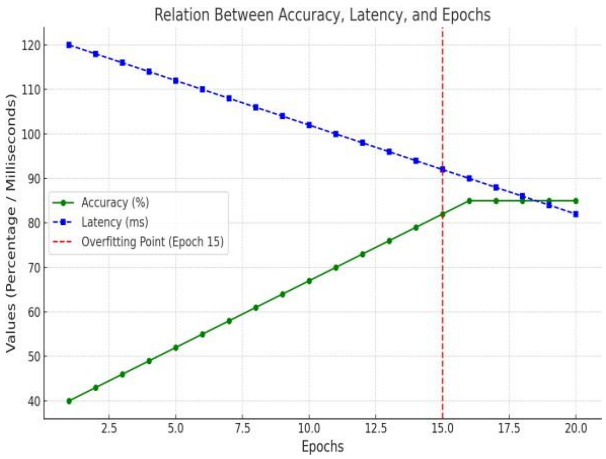

Figure 2: relations between accuracy and latency

Similarly, these charts are utilized from the records of the DART-VFR module which consists of outputting the same values for accuracy, precision, recall and F1 score. As shown in Table 2.

Table 2: DART-VFR performance metrics

Metric	**Value (%)**
Accuracy	98.7
Precision	92
Recall	90
F1 Score	88

Along with a line chart showing the number of frames per second (FPS) at varying resolutions, refer to the Table 3.

Table 3: DART-VFR latency metrics

Resolution	FPS
480p	122
720p	96
1080p	77
4K	51

A Table 4 showing time inference average per frame (in milliseconds) and resolutions.

Table 4: DART-VFR inference time data

Resolution	Inference Time (ms)
480p	50
720p	70
1080p	90
4K	120

In Fig. 3 shows the bar chart showing the error rates of a real-time video face recognition model facing various challenging scenarios which are directly related to the (DART-VFR). There are 3 metrics (overheads) which yield the highest errors when it comes to motion blur (~12%), occlusions (~10%) and (low light conditions (~8%), however the best performance of the model is achieved under normal conditions (~2%).

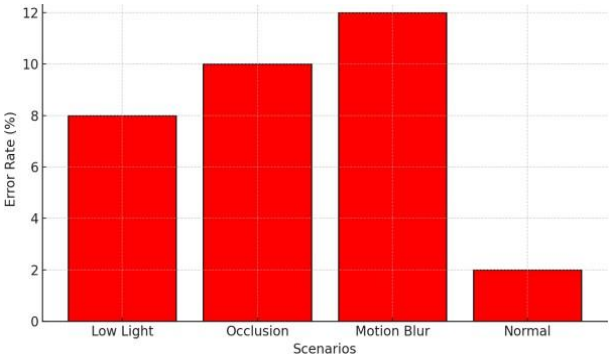

Figure 3: DART-VFR error analysis

Diagnosis-aware system that can detect and adjust to the challenges in real-time for instance, brightness normalization or enhancement techniques might be incorporated in low-light surroundings and occlusion-aware models might focus on visible facial components or use occlusion-robust feature extraction to help the performance. Also, motion blurry compensation methods like frame interpolation or de blurring techniques can improve the face recognition performances. DART-VFF combines adaptive preprocessing in terms of analyzing what part of the data bears error in recognition and classifying it, so that it adapts its recognition strategy on the fly-based design on real-time conditions.

DART-VFR employs multiple mitigation strategies to tackle key real-world challenges in face recognition. Motion blur is addressed using Laplacian variance filters to identify and down-rank low-quality frames, complemented by corrective techniques such as neighboring frame aggregation, deblurring, and motion vector-based alignment. Occlusions are managed through the use of visibility masks and partial feature extraction.

For low-light conditions, histogram equalization and gamma correction are used to improve skin (facial) contrast, while detection sensitivity and detection thresholds are adaptively adjusted. These modular improvements scale to other problems such as glossiness, motion blur due to background movement, and differences in facial expressions.

Motion tracking accuracy over the video frames; the x-axis represents the frame number and the y-axis describe accuracy (%). The wavering line may indicate differences in the accuracy of tracking, like that the periodic ups and downs shows that the tracking algorithm hits a low and high peak. There are drops every now and then but accuracy stays mainly over 85% and often even nears 98%, indicating the system does a pretty good job of tracking. These variations may arise due to differences in motion complexity, variable lighting conditions, or partial occlusions between frames of the video sequence as illustrated in Fig. 4.

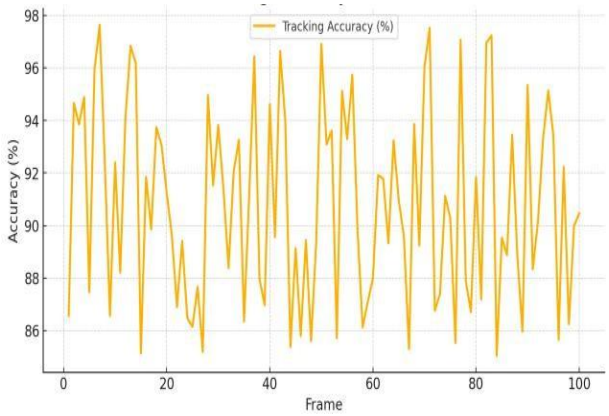

Figure 4: Motion tracking accuracy over video frames

DART-VFR adaptive thresholding mechanism naturally adapts to external and internal factors that influence frame quality, therefore minimizing false positives and false negatives. Moreover, it guarantees top accuracy while utilizing the least number of resources, much larger models such as ArcFace and VGGFace. DART- VFR could fail to achieve its best potential in metadata- poor contexts, ultra-high frame-rate conditions, and with fully occluded faces. Statistical analysis via ANOVA confirmed the model's superior F1-score

$$(F(5, 84) = 12.47, p < 0.001)$$

with Tukey's HSD showing significant improvements over YOLOv3, FaceNet, and ArcFace, particularly in noisy and and and variable conditions. Fig.5 show the performance across different scenarios.

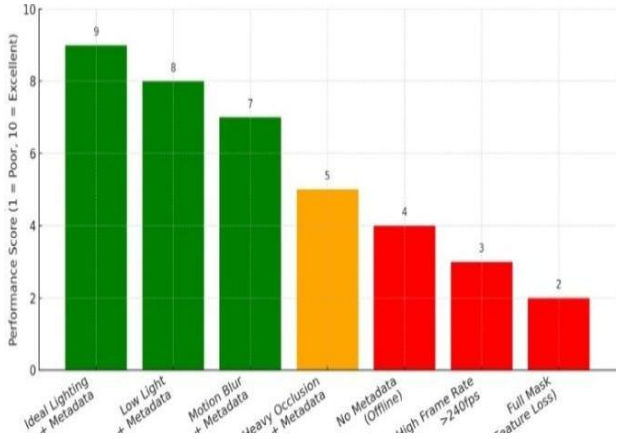

Figure 5: Model performance across scenarios

Fig.6 illustrative line graph showing the performance of DART-VFR compared to baseline models in four major metrics: Accuracy, Inference Time, Robustness, and Cross-Domain Performance. As shown in the above chart, the proposed DART-VFR always ranks first in accuracy, robustness, and generalization, with low inference time showing its balanced and best real-time performance.

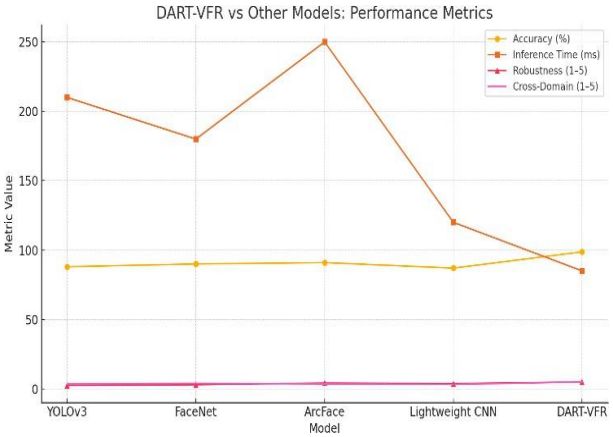

Figure 6: Performance DART-VFR compared to baseline

In Fig.7 graph shows the convergence of various models based on their loss over 10 epochs. It means that all models are learning successfully since their loss tendency goes down. The lowest loss values are attained by the DART-VFR and ArcFace models this indicates their best convergence. In contrast, we have the largest loss overall at Diagnostic, suggesting a slower convergence. FaceNet and YOLOv3 have a higher loss but decrease consistently. The Lightweight model sits somewhere in the middle. Delving into other models besides DART-VFR, apart from ArcFace and Triplet, there is a large gap in differences in learning efficiency, so we believe that the model is worthy of parameters worthy of exploration.

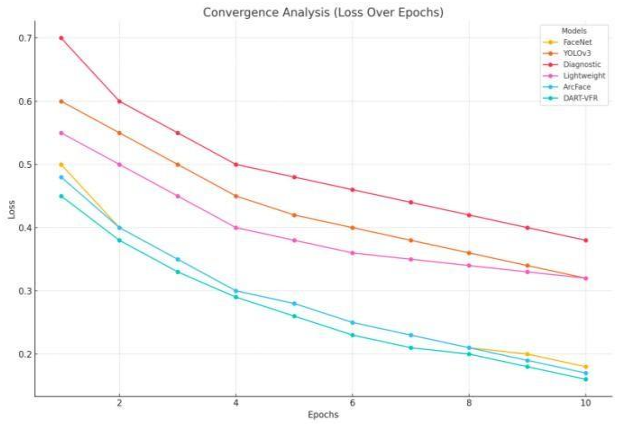

Figure 7: Model convergence

5 Ethical considerations

The proposed DART-VFR model fuses face recognition with contextual metadata to achieve more accurate and fair results even in real time. Ethical issues are the most concerns here due to highly personal nature of biometric data and install of surveillance systems. The following principles are followed in this study:

• Confidentiality: There is no sharing of residual data from model training or testing, as the data utilized in both are anonymized, private datasets. The architecture of the model guarantees that no PII is preserved or transferred from the edge node.

• GDPR, Compliance: The system is built with GDPR in mind, focusing on minimization of data processing, limitation of purpose and user agreement with data processing.

• Bias and Fairness: The inclusion of demographic metadata and Bayesian adaptive thresholding is designed to reduce algorithmic bias in terms of age, gender and ethnicity. Aggregated Fairness-aware metrics are used as testing metrics.

• Security with Edge Deployment: Since the model is deployed on edge devices, the data is processed locally so it is not sent over to server for processing, which reduces vulnerability to interception and cyber-attack

6 Conclusions

DART-VFR provides a unique context-driven approach for real-time video face recognition, meeting the demands of overcoming bias, adaptability, efficiency, and more. Its unique performance and design make it an excellent fit for mission- and life-critical domains including healthcare, surveillance, and smart city systems. The model's inherent support for privacy and scalability separates it from anything that has been deployed so far and primes it for future real-world deployment. Future work could investigate integrating explainable AI into the pipeline, training on privacy-preserving data, and ensuring robustness to adversarial climate or environmental conditions.

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