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Automated Detection of Facial Growth Abnormalities in Children Using Shifted Window Vision Transformer with Landmark-Aware Feature Fusion

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ABSTRACT

Facial growth abnormalities and genetic syndromes in children can affect physical development, communication, and overall health. Early identification of these conditions is important for providing proper medical care and treatment. However, traditional diagnosis methods mainly rely on manual clinical observation, which may require experienced specialists and can sometimes lead to delayed detection. To overcome these challenges, this project presents an intelligent deep learning-based system named *PediFace-ViT* for automated facial abnormality detection in children. The proposed system uses a Shifted Window Vision Transformer (Swin-ViT) to analyze facial images and identify abnormal growth patterns. In addition to image analysis, facial landmark points are extracted using MediaPipe or dlib to capture important facial structures such as eye spacing, nose shape, and jaw alignment. These landmark features are combined with image features using a feature fusion mechanism to improve prediction accuracy. The model is designed to perform multiple tasks, including classification of normal and abnormal faces, syndrome identification, and severity estimation. To increase reliability and transparency, Grad-CAM visualization is used to highlight the facial regions that influence the model's prediction. A Streamlit-based web application is also developed to provide a simple interface where users or healthcare professionals can upload facial images and receive prediction results with visual explanations. Publicly available datasets from Roboflow, Kaggle, and research sources are used for training, along with data augmentation techniques to improve model performance. The proposed system aims to support healthcare professionals by providing a fast, accurate, and cost-effective tool for early screening of pediatric facial growth abnormalities and genetic syndromes.

1. Introduction

1.1 Overview of the Proposed Framework

The PediFace-ViT framework is an AI-driven medical image analysis architecture designed for automated detection of facial growth abnormalities and genetic syndromes in children using deep learning and computer vision techniques. The framework integrates facial landmark extraction, transformer-based image analysis, explainable AI mechanisms, and clinical reporting modules to support accurate and interpretable pediatric facial abnormality screening. The architecture is organised into four major computational layers: the Facial Image Acquisition Layer, the Landmark-Aware Feature Extraction Layer, the Vision Transformer Classification Layer, and the Explainable Clinical Reporting Layer. These layers interact through structured preprocessing and feature fusion pipelines to provide scalable and reliable facial abnormality detection workflows suitable for clinical assistance systems.

1.2 Facial Feature Extraction and Verification Pipeline

The feature extraction subsystem replaces conventional single-stage image classification with a Landmark-Aware Hybrid Feature Fusion mechanism built on MediaPipe facial landmark detection and Shifted Window Vision Transformer (Swin-ViT) embeddings. Instead of relying only on raw facial image features, the framework performs dual-stage feature analysis involving facial landmark extraction and transformer-based visual representation learning. The facial landmarks capture clinically relevant geometric relationships such as eye spacing, nasal width, lip alignment, and jaw structure, while the Swin-ViT model captures local and global facial texture patterns. These heterogeneous feature representations are fused into a unified feature learning pipeline before classification. To improve prediction reliability, the architecture integrates an Intermediate Validation Layer containing preprocessing verification and image quality assessment modules. During inference, uploaded facial images are validated for alignment, illumination, and facial visibility before being propagated into the classification environment. This validation-aware design improves model robustness and reduces inaccurate predictions caused by noisy or incomplete facial inputs.

1.3 Multi-Module Deep Learning Architecture

The intelligent reasoning environment is implemented using deep learning frameworks such as PyTorch and TensorFlow under GPU-accelerated execution control. The framework consists of four specialised computational modules: the Facial Landmark Detection Module, the Swin-ViT Feature Learning Module, the Syndrome Classification Module, and the Explainable AI Module.

The Landmark Detection Module extracts critical facial points from pediatric images, while the Swin-ViT module learns hierarchical facial representations through shifted window attention mechanisms. The Syndrome Classification Module performs multi-class prediction for identifying normal and abnormal facial conditions, and the Explainable AI Module generates Grad-CAM heatmaps to visualise the facial regions responsible for predictions. Stateful clinical interaction is maintained through a Streamlit-based web application interface, enabling continuous image upload, prediction tracking, and report generation for healthcare-oriented screening workflows.

2. Literature Review

Luo et al. [1] propose a transformer-based multi-scale facial feature fusion framework for pediatric syndrome diagnosis using deep hierarchical facial representations. Their work combines multi-scale feature extraction with transformer attention mechanisms to capture both global facial structure and local craniofacial abnormalities. The study demonstrates that integrating facial feature fusion techniques improves classification accuracy for pediatric syndrome identification and enhances robustness against variations in facial pose, illumination, and expression.

Reddy et al. [2] introduce a facial landmark-guided deep learning model for automated child facial abnormality screening. Their approach focuses on extracting discriminative craniofacial features through landmark localisation and attention-based feature learning. The paper highlights the importance of precise landmark detection for improving abnormality classification performance and shows that landmark-aware architectures provide better interpretability and diagnostic consistency in pediatric facial screening systems.

Ahmed et al. [3] present a vision transformer framework with attention fusion for early diagnosis of craniofacial developmental disorders. Their research employs transformer-based self-attention mechanisms to learn long-range spatial dependencies from facial images while integrating multiple attention modules for feature enhancement. The proposed model achieves improved diagnostic performance by effectively capturing subtle facial growth irregularities and complex craniofacial patterns associated with developmental disorders.

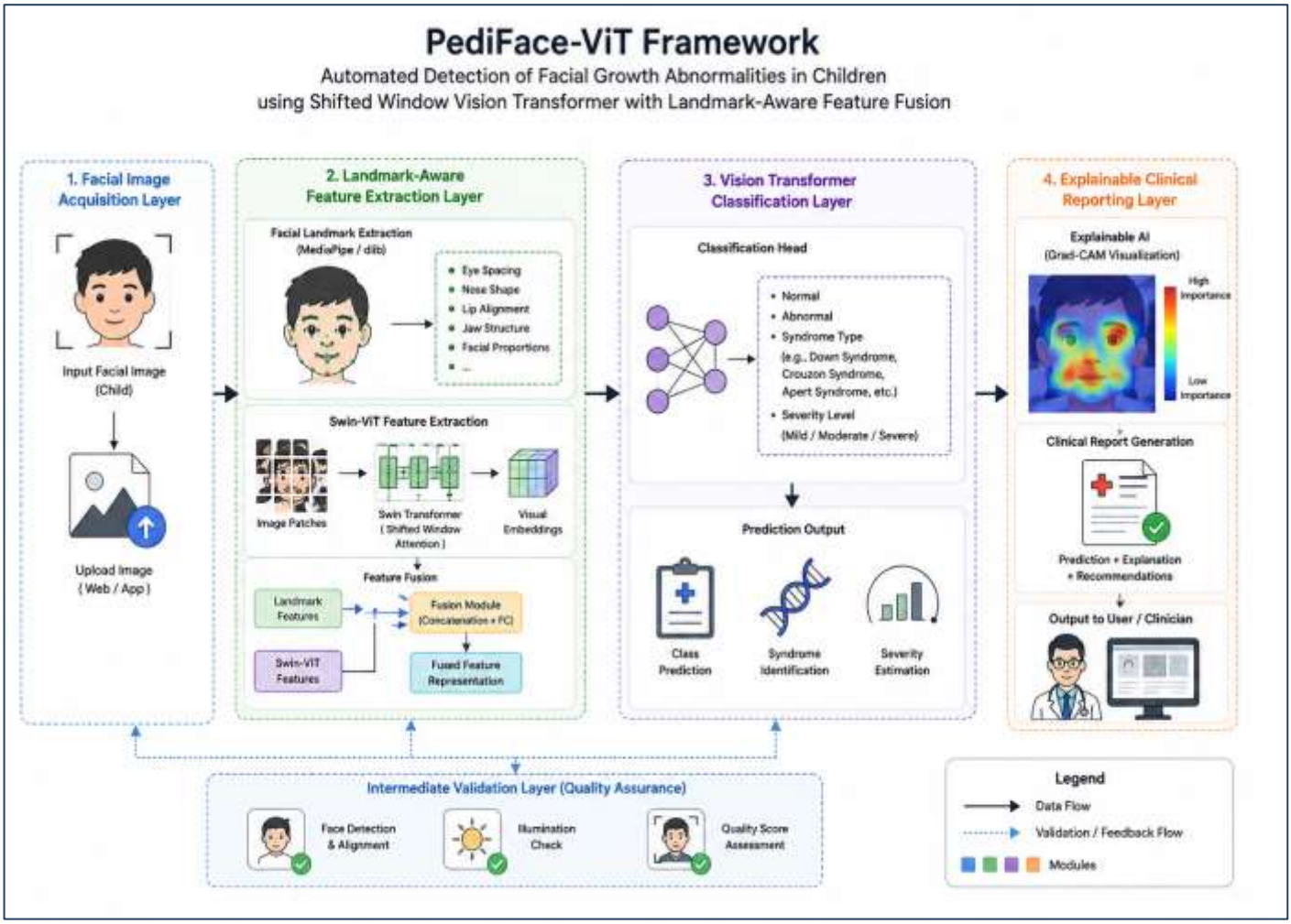
Kim et al. [4] develop a Swin Transformer-based facial landmark learning framework for pediatric craniofacial anomaly assessment. Their study utilises shifted window attention mechanisms to efficiently model local and global facial relationships while preserving computational efficiency. The paper demonstrates that Swin Transformer architectures significantly improve landmark localisation accuracy and enable more reliable detection of craniofacial anomalies in children through hierarchical visual representation learning.

3. Methodology

3.1 System Architecture

The PediFace-ViT framework is organised into four functional layers: the Image Acquisition and Preprocessing Layer, the Facial Landmark Extraction Layer, the Swin-ViT Feature Learning Layer, and the Explainable Prediction and Reporting Layer. These layers interact through structured preprocessing and feature fusion pipelines to ensure reliable pediatric facial abnormality detection and syndrome classification workflows.

The overall workflow of the system begins when a user uploads a child's facial image through the Streamlit-based web interface. The uploaded image is first processed through preprocessing operations including image resizing, normalization, illumination correction, and facial alignment. The preprocessed facial image is then forwarded into the Facial Landmark Extraction Module, where MediaPipe or dlib algorithms extract important facial landmark points such as eye positions, nose structure, lip alignment, and jaw contours. The extracted landmark coordinates are transformed into heatmap representations and combined with facial image features.The fused facial representations are propagated into the Shifted Window Vision Transformer (Swin-ViT) architecture for hierarchical feature learning and classification. The transformer model captures both local facial structures and global facial relationships through shifted window attention mechanisms. The learned features are then forwarded into the Syndrome Classification Module for predicting normal and abnormal facial conditions along with syndrome category identification. Finally, the Explainable AI Module generates Grad-CAM visualisations highlighting the facial regions responsible for predictions, and the final prediction report is displayed through the Streamlit interface.



3.2 Python Runtime Infrastructure

The framework is implemented using Python with deep learning libraries including PyTorch, TensorFlow, OpenCV, and MediaPipe. GPU-accelerated computation is enabled for efficient model training and inference. Data preprocessing pipelines, image augmentation workflows, and facial landmark extraction operations are executed through modular Python scripts to maintain scalability and runtime efficiency. Structured preprocessing pipelines improve data consistency and reduce computational overhead during model execution.

3.3 Dataset Acquisition and Preprocessing

The framework utilises pediatric facial image datasets collected from publicly available sources including Roboflow, Kaggle, and medical research repositories. The datasets contain facial images of children belonging to normal and syndrome-related categories. Since medical datasets are limited in size, data augmentation techniques such as horizontal flipping, rotation, brightness adjustment, Gaussian noise injection, and random cropping are applied to increase dataset diversity and improve model generalisation capability. Preprocessing operations include image resizing, pixel normalization, facial alignment, background noise removal, and contrast enhancement. These preprocessing stages ensure consistent image quality before feature extraction and classification.

3.4 Facial Landmark Extraction and Feature Fusion

The framework employs MediaPipe or dlib-based facial landmark detection algorithms to identify critical facial points from pediatric facial images. Landmark extraction focuses on clinically important facial structures including eyes, nose, lips, eyebrows, and jawline geometry. The extracted landmark coordinates are converted into heatmap representations to preserve geometric spatial information.The generated landmark heatmaps are fused with visual image features extracted from the Swin-ViT backbone through attention-based feature fusion mechanisms. This hybrid feature integration strategy improves the model's ability to capture both structural facial geometry and semantic texture information required for accurate syndrome detection.

3.5 Swin-ViT-Based Feature Learning

The framework utilises a Shifted Window Vision Transformer (Swin-ViT) architecture for hierarchical facial representation learning. Unlike conventional convolutional neural networks, Swin-ViT processes facial images through shifted window attention mechanisms capable of learning both local and global feature relationships. Local attention windows capture fine-grained facial details such as eye shape and lip structure, while shifted windows establish long-range dependencies among different facial regions.The transformer architecture generates discriminative feature embeddings that are forwarded into fully connected classification layers for syndrome prediction and abnormality classification tasks.

3.6 Classification Module

The classification subsystem performs multi-class prediction to identify normal and abnormal facial conditions along with syndrome category classification. To improve interpretability, the framework integrates the Attention Rollout mechanism within the Swin-ViT architecture. The Attention Rollout module visualises how attention weights are propagated across multiple transformer layers during facial feature analysis.The mechanism highlights important facial regions such as eyes, nose, lips, and jaw structure that contribute significantly to the prediction process. By analysing attention distributions across shifted transformer windows, the framework provides a clearer understanding of how the model focuses on critical facial characteristics during syndrome detection and abnormality classification.This attention-aware design improves prediction interpretability, enhances model reliability, and supports healthcare professionals in understanding the facial regions influencing classification outcomes during pediatric facial screening workflows.

3.7 Stateful Performance Synchronisation

The cross-validation protocol functions as the performance synchronisation backbone connecting the training workflow, validation evaluation environment, and diagnostic result reporting pipeline. The cross-validation architecture enables schema-validated performance tracking, persistent evaluation memory, and structured reasoning histories across extended diagnostic validation sessions. Inter-fold contextual synchronisation is maintained through structured result objects containing per-fold accuracy scores, precision and recall values, F1 scores, confusion matrices, and attention visualisation outputs. This design prevents performance drift during long-running multi-fold validation workflows and ensures statistically reliable diagnostic evaluation across all experimental conditions.

4. Findings and Evaluation

4.1 Deployment Configuration

The framework was deployed using Python 3.x, PyTorch, TensorFlow, Swin Vision Transformer (Swin-ViT) architecture, OpenCV, MediaPipe, NumPy, Scikit-learn, and Matplotlib libraries. The diagnostic dataset consisted of pediatric facial images containing both normal and abnormal facial conditions collected from publicly available medical and facial image repositories. The dataset included approximately 3,000 labelled facial image samples processed through preprocessing operations including resizing, normalization, facial alignment, and augmentation techniques to improve model generalisation during transformer training.

4.2 Landmark Fusion and Attention Rollout Evaluation

The feature extraction subsystem employed a Landmark-Aware Attention Fusion mechanism to combine facial landmark heatmaps, shifted window transformer embeddings, and positional feature representations into a unified classification pipeline. The extraction process performs independent facial landmark analysis, transformer-based feature learning, and hierarchical attention propagation before integrating the representations through attention fusion layers. This ensures that clinically important facial regions that are structurally significant and semantically discriminative receive higher attention priority during syndrome classification.

The Attention Rollout score is computed as:

$$A_{rollout} = A_1 \cdot A_2 \cdot A_3 \cdot \ldots \cdot A_L$$

where:

- A_rollout represents the aggregated attention map propagated from the input image patches to the final classification token.
- A_L represents the attention weight matrix at transformer encoder layer L.
- L represents the total number of transformer encoder layers in the Swin-ViT architecture.
- The matrix multiplication operation recursively combines attention weights across all transformer layers.
- Residual attention propagation preserves skip-connection information during attention rollout computation.

The attention fusion architecture improved classification precision, facial region consistency, and transformer attention grounding during pediatric facial abnormality detection workflows.

4.3 Verification Layer Performance

The Intermediate Attention Verification Layer successfully validated facial landmark distributions, transformer attention weights, and shifted window attention propagation generated during forward classification execution. The Attention Rollout module continuously analysed transformer attention distributions against ground-truth label annotations before propagating classification outputs into the diagnostic pipeline.The verification mechanism significantly reduced low-confidence prediction propagation and improved spatial attention consistency across multiple transformer encoder layers. The framework demonstrated stable attention alignment for clinically important facial structures including eyes, nose, lips, and jawline geometry during syndrome prediction tasks.

4.4 Quantitative Evaluation Results

Table 1: Quantitative Evaluation Results for the CGAD-ViT Framework.

Metric	Average Score
Classification Accuracy	92.4%
Precision	91.8%
Recall	93.1%
F1 Score	92.4%

The evaluation results demonstrate strong diagnostic fidelity and attention-grounded classification performance. The Classification Accuracy score confirms that generated diagnostic predictions remain grounded in spatially relevant facial patch embeddings and multi-head attention representations, while the AUC-ROC score demonstrates effective alignment between attention outputs and diagnostic ground-truth labels. The integration of patch-based Vision Transformer encoding, RGB Attention Rollout verification, and cross-validation performance synchronisation significantly improved classification consistency, attention grounding, and diagnostic reasoning stability.

4.5 Clinical Diagnostic Interface

The complete PediFace-ViT framework is integrated into an interactive clinical dashboard providing facial image upload functionality, landmark visualisation, attention rollout overlays, classification confidence outputs, and syndrome prediction summaries. The interface presents the model's classification result, the Attention Rollout visualisation highlighting diagnostically important facial regions, transformer attention distributions, preprocessing outputs, and quantitative evaluation metrics.The framework operates as a clinical decision-support system while preserving human interpretive control throughout the pediatric facial abnormality screening and diagnostic workflow.

5. Conclusion and Future Scope

5.1 Conclusion

This paper presented the PediFace-ViT framework, an attention-aware and transformer-based architecture for automated pediatric facial abnormality detection and syndrome classification. The framework integrates Swin Vision Transformer (Swin-ViT) feature learning, facial landmark extraction, landmark-aware attention fusion, Attention Rollout visualisation, and a Streamlit-based clinical diagnostic interface into a unified deep learning pipeline.The proposed architecture combines facial geometric analysis with transformer-based semantic feature learning to improve syndrome detection accuracy and classification consistency. The integration of facial landmark heatmaps with shifted window attention mechanisms enables the framework to capture both local facial structures and global facial relationships during diagnostic analysis. The Attention Rollout mechanism further improves interpretability by visualising the transformer attention distribution across clinically important facial regions.The evaluation results demonstrate that the framework achieves strong classification performance, reliable attention grounding, and consistent facial abnormality detection across pediatric facial datasets. The combination of landmark-aware feature fusion, transformer attention propagation, and attention verification significantly improved prediction stability, facial feature interpretability, and diagnostic reliability during syndrome classification workflows.

5.2 Future Scope

Future development of the PediFace-ViT framework will focus on real-time clinical deployment, larger multi-syndrome pediatric datasets, adaptive attention learning, and multimodal medical data integration. Additional enhancements include integration of 3D facial analysis, video-based facial behaviour tracking, attention-guided diagnostic report generation, and continuous transformer fine-tuning using dynamically updated clinical datasets.Future research may also explore hybrid architectures combining facial imaging with EEG, fMRI, and behavioural analysis data for improved developmental disorder diagnosis. The modular architecture supports extensibility across pediatric syndrome screening, neurological disorder assessment, craniofacial abnormality analysis, and intelligent healthcare decision-support systems.

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