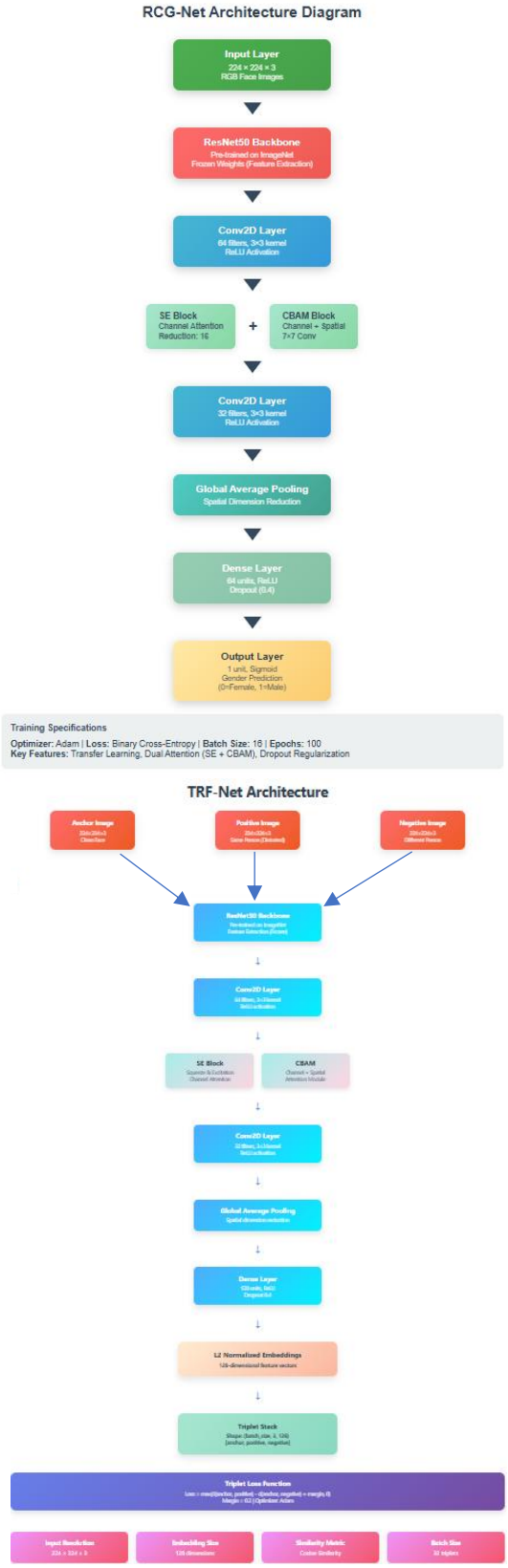
**COMSYS-2025 - The 6th International Conference on Frontiers in Computing and Systems (COMSYS-2025)**

**Theme: Robust Face Recognition and Gender Classification under Adverse Visual Conditions**

# 1-page technical summary:

## Task A: RCG-Net - ResNet50-Based Gender Classification Network

RCG-Net presents a sophisticated deep learning architecture for binary gender classification from facial images, combining transfer learning with advanced attention mechanisms in a unified framework. The model employs a frozen ResNet50 backbone pre-trained on ImageNet as a robust feature extractor for 224×224×3 RGB input images, followed by custom enhancement layers including a 64-filter convolutional layer, a Squeeze-and-Excitation (SE) block for channel-wise attention with reduction ratio 16, a Convolutional Block Attention Module (CBAM) for dual channel and spatial attention using 7×7 convolutions, another 32-filter convolutional layer, global average pooling, a 64-unit dense layer with 0.4 dropout regularization, and finally a single-unit sigmoid output layer for binary classification (0=Female, 1=Male). The model is trained using Adam optimizer with binary cross-entropy loss over 100 epochs with batch size 16, incorporating ResNet50-specific preprocessing with mean centering and scaling. The dual attention mechanism significantly enhances feature selection by emphasizing important channels through SE blocks while simultaneously focusing on relevant spatial regions via CBAM, resulting in improved classification accuracy and demonstrating the effectiveness of combining established CNN backbones with modern attention mechanisms for robust gender classification tasks in computer vision applications, with comprehensive evaluation including confusion matrix analysis, classification reports with precision/recall/F1-score metrics, and training curve visualization.




## Task B: TRF-Net: Triplet ResNet Fusion Network for Robust Face Recognition

**TRF-Net** is a deep learning architecture designed for robust face recognition that combines transfer learning, attention mechanisms, and triplet loss optimization to handle challenging scenarios including distorted and degraded facial images. The network leverages a pre-trained ResNet50 backbone as a feature extractor, followed by custom convolutional layers enhanced with Squeeze-and-Excitation (SE) blocks and Convolutional Block Attention Module (CBAM) for improved feature representation, where SE blocks perform channel-wise attention through global average pooling and fully connected layers, while CBAM provides both channel and spatial attention mechanisms to focus on discriminative facial features. The training methodology employs triplet loss with a margin of 0.2, where each training sample consists of an anchor image (clean face), a positive image (distorted version of the same person), and a negative image (different person), enabling the network to learn robust embeddings that minimize intra-class distance while maximizing inter-class separation. The triplet generation strategy specifically pairs clean facial images with their corresponding distorted variants (including rainy, blurry, or other degradations) as positive samples, ensuring the model learns invariance to common image distortions, while processing 224×224 RGB images normalized to [0,1] range using Adam optimizer with custom accuracy metrics that measure the proportion of triplets where the anchor-positive distance is smaller than the anchor-negative distance. The network outputs 128-dimensional L2-normalized embeddings that capture essential facial characteristics in a compact representation, and for inference, TRF-Net computes embeddings for query faces and matches them against a reference database using cosine similarity, achieving face recognition by identifying the closest match above a predefined threshold with the ability to reject unknown faces when similarity scores fall below the threshold, making it particularly suitable for real-world applications where image quality may be compromised due to environmental factors or acquisition conditions.