1 Updated Pipeline

2 Methodology

The proposed framework enhances the performance of CNN-based classification by integrating multiple backbone networks, adaptive feature selection, and a priority-based ensemble strategy. The methodology comprises the following sequential stages:

2.1 Data Preprocessing

The input dataset undergoes standard preprocessing steps as given in the mentioned paper.

2.2 Multi-Backbone Feature Extraction

To capture diverse and complementary feature representations, we employ multiple pretrained convolutional neural network (CNN) backbones such as DenseNet121, ResNet50, EfficientNet-B0, and InceptionV3, etc. (Choose 3-4 atleast). Each backbone extracts high-level feature descriptors from the final convolutional or global pooling layers.

Use the channel attention also as described in the paper.

Formally, given an input image I, the feature set extracted from backbone B_j (after channel attention) is represented as:

$$F_j = B_j(I), \quad j = 1, 2, \dots, k$$

where k denotes the total number of CNN backbones used. The extracted features from all backbones are concatenated to form a comprehensive feature space:

$$F = [F_1 \parallel F_2 \parallel \dots \parallel F_k]$$

2.3 Feature Selection via mRMR and Adaptive Grey Wolf Optimization (AGWO)

The concatenated feature space F may contain redundant or irrelevant attributes, leading to computational inefficiency and degraded classifier performance. To address this, a two-stage feature selection process is employed.

2.3.1 Stage 1: mRMR Filter Ranking

Initially, the features are ranked using the Minimum Redundancy Maximum Relevance (mRMR) criterion. This filter-based method selects features that maximize class relevance while minimizing inter-feature redundancy.

2.3.2 Stage 2: Adaptive Grey Wolf Optimization (AGWO)

The ranked feature set is further refined using AGWO, a population-based metaheuristic inspired by grey wolf hunting behavior. Here we are replacing genetic algorithm by grey wolf optimizer only.

2.4 Multi-Classifier Learning

The optimized feature subset F^* is provided as input to multiple classifiers to enhance robustness. In this work, we utilize Support Vector Machine (SVM), Random Forest (RF), Gradient Boosted Trees (XGBoost), K-Nearest Neighbors (KNN), and Logistic Regression (LR). Each classifier produces a probabilistic prediction vector $p_i(c)$, where $p_i(c)$ denotes the probability assigned to class c by classifier i.