A Hybrid Feature Fusion Approach With Optimized Adaptive SVM For High-Performance Multi-Class Cervical Image Classification

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- Hybrid Feature Extraction, Adaptive Support Vector Machine, Multi-Class Image Classification, GLCM, HOG, LBP, PCA, Hyperparameters

Abstract

Precise and effective Hybrid Feature Extraction multi-class image classification is still an arduous problem, particularly in cases with high intra-class variability and inter-class similarity. In this paper, a new hybrid feature fusion approach combined with an Optimized Adaptive Support Vector Machine (OASVM) is proposed to improve the classification capability of complicated cervical image sets. The model that is proposed here combines manually engineered features of Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP), representing both spatial gradients and texture of the images. These features are normalized and combined into a strong hybrid descriptor, and then their dimensionality is reduced using Principal Component Analysis (PCA) to remove redundancy and enhance computational efficiency.

An Adaptive SVM classifier is optimized subsequently with a hybrid kernel function that adaptive weights together linear, RBF, and sigmoid kernels. The tailored kernel expression enables the model to generalize more effectively across varied feature distributions. Grid search is also utilized to fine-tune the classifier to determine the best hyperparameters, substantially enhancing classification performance. Experimental tests prove that the designed OASVM model performs better than general-purpose classifiers such as Logistic Regression, Random Forest, and traditional SVM in accuracy, precision, recall, and F1-score. The system is able to obtain the accuracy of 95.2% on a difficult multi-class cervical image database, which proves the superiority of the hybrid feature approach and adaptive learning process. This work adds a scalable and trustworthy answer for real-world image classification tasks, especially in applications such as medical imaging, agriculture, and object detection, where accuracy and interpretability are of utmost importance.

1. Introduction

Cervical cancer is still among the top causes of death among women globally, especially in areas where there is limited availability of screening and diagnostic facilities. Detection of precancerous and cancerous lesions at an early stage is of vital importance for enhancing patients' outcomes and lowering mortality rates. Historically, cytology-based screening methods like the Pap smear and visual inspection procedures like colposcopy have been used to detect cervical intraepithelial neoplasia (CIN) and carcinoma in situ. These methods, though dependent on trained observer interpretation and affected by inter-observer variation and availability of resources [1], are not based on biological markers and therefore lack specificity. Automated image analysis by machine learning (ML) and deep learning (DL) methods has shown significant promise in cervical cancer detection and classification in recent times. Transfer learning architectures like ResNet, VGG, and DenseNet have reported impressive results on public benchmarks such as SIPaKMeD and Herlev. For example, comparing 16 pre-trained DL models showed that ResNet50 had 95% accuracy on 7-class Herlev classification and VGG16 had 99.95% on 5-class SIPaKMeD tasks [2]. Similarly, a CNN with reduced size called CCanNet had 98.53% accuracy with much fewer parameters, ensuring the possible deployment in real-time using limited resources [3].

These developments notwithstanding, DL methods tend to demand large quantities of labeled data and high computational capacity. To tackle this, a few hybrid models fusing engineered attributes with DL-harvested representations have been introduced. In one such work, a feature extractor from VGG16 mixed with an AutoInt module was used, which reached more than 99.9% class-level accuracy on the cervical image dataset [4]. A different direction focused on using a hybrid CNN-transformer-GRU network called CerviFusionNet, which demonstrated strong performance on high-resolution images of cervics [5]. The latest transformer-based models have also shown the potential for generalization across different imaging modalities in colposcopy using risk-profile data [6]. Such methods, although having impressive quantitative performance, have limited interpretability and do not perform well on class imbalance for dysplasia severity levels from normal to carcinoma in situ. Not many studies target specifically to differentiate between the six histologically relevant classes ('carcinoma_in_situ', 'light_dysplastic', 'moderate_dysplastic', 'severe_dysplastic', 'normal_columnar', and 'normal_intermediate'). To bridge this gap, hybrid feature fusion approaches that combine domain-specific descriptors (e.g., GLCM, LBP, and HOG) with kernel-based classifiers optimized have been recently discussed [7][8]. These methods seek to leverage the interpretability of hand-crafted descriptors and the adaptability of adaptive classifiers.

Inspired by these advances, this work introduces a new hybrid feature fusion method that combines texture, gradient, and intensity descriptors with subsequent dimensionality reduction using PCA. Central classifier is a maximum Adaptive Support Vector Machine (ASVM) with a hybrid kernel function containing linear, RBF, and sigmoid elements. The ASVM's weight parameters are optimized using grid search. This design is particularly geared towards discriminating the six cervical classes correctly with high accuracy, even when class imbalance and small sample sizes exist. Experimental comparisons show that our Optimized ASVM substantially outperforms baseline ML classifiers such as SVM, Random Forest, and Logistic Regression along with current DL-based models on the identical dataset.

The main contributions of this research are:

1. A hybrid descriptor integrating GLCM, HOG, and LBP features optimized for cervical cell morphology.

2. An optimized ASVM classifier with a new hybrid kernel, with flexible decision boundaries well-suited to capture complicated class differences.

3. Strict testing on six target classes of cervical dysplasia, demonstrating better performance in accuracy, recall, precision, and F1-score, with interpretability and lower computational complexity.

This work fills essential gaps in multi-class cervical image classification and presents a simple and reliable solution for disease screening from automation. The rest of the paper is organized as follows: Section 2 discusses related work, Section 3 outlines the proposed methodology, Section 4 provides experimental results, and Section 5 concludes with directions for future research.

2. Related works

Ach Khozaimi et al. [9] suggest a hybrid image improvement method with PMD Filter and CLAHE for enhancing cervical cancer classification based on Pap smear images. The technique is used to enhance image quality before classification, increasing overall performance in the detection of cancerous patterns. The technique was tested on cervical datasets and demonstrated better segmentation and identification of disease areas. Elayaraja P et al. [10] introduce an automated diagnosis approach that utilizes a Genetic Algorithm feature selection in conjunction with a CANFIS (coactive neuro-fuzzy inference system) classifier. The synergy between evolutionary computation and fuzzy logic provides a great level of flexibility and interpretability, thereby resulting in improved prediction accuracy for cervical cancer classification. Saurabh Saini et al. [11] propose a hybrid descriptor technique that integrates deep learning and handcrafted feature extraction with feature reduction to improve cervical cancer classification from colposcopy images. Their system utilizes a deep convolutional network to learn spatial information with the inclusion of texture descriptors, which offers higher classification accuracy. Nugroho Suhandono and Siti Nurmaini [12] introduce a MLP-based classifier based on hybrid features extracted from GLCM, LBP, and MobileNetV2 embeddings. This combination utilises both texture and deep features to effectively classify cervical precancerous conditions. The model exhibited enhanced sensitivity and specificity. Haotian Feng et al. [13] investigate an innovative method involving multi-modality and temporal image analysis for tracking cervical cancer treatment responses. The research utilizes MRI and PET information as well as machine learning algorithms, providing a detailed picture of the efficacy of treatment as well as long-term disease progression. Contrast enhancement is used by Siqi He et al. [14] in creating an SVM classifier for cervical histopathology images from combined texture and morphological features. Their manually designed feature representation enables the model to distinguish between patterns of tissue, providing improved diagnostic assistance in early detection applications. Mengdi Tang et al. [15] propose a hybrid approach that uses a Conditional Tabular GAN (CTGAN) for generating synthetic data, augmenting the training dataset and reducing class imbalance. This approach, combined with a deep neural network, enhances the accuracy of cervical cancer detection.

Madhura Kalbhor and Swati Shinde [16] introduce a hybrid classification system named ColpoClassifier for cervigram automated analysis. It has both statistical and deep learning attributes and carries out multi-class classification, which is beneficial in real-time screening systems. Mehran Ahmad et al. [17] apply hybrid deep learning methods to early diagnosis of oral squamous cell carcinoma, similar in technique to cervical cancer detection. They employ a combination of CNNs, texture features, and handcrafted techniques, especially pin-pointing the stability of hybrid models in histopathological image analysis. Badiea Abdulkarem Mohammed et al. [18] suggest hybrid diagnostic methods based on Whole Slide Images (WSIs) and feature fusion approaches for cervical cancer detection. Their work focuses on large-scale image processing and deep feature combination to enhance detection accuracy in clinical-grade purposes. Cheng C. et al. [19] discuss cervical cancer image processing through deep learning methods with a focus on CNN-based segmentation and classification workflow. Their research provides a basis for enhanced accuracy in detecting abnormal areas in cervical images. Talpur D. B. et al. [20] present DeepCervixNet, an expert deep learning model for Pap smear image classification. The model is specifically designed to identify subtle cell abnormalities with improved sensitivity and has been highly effective in benchmark tests. Bueno Crespo A. et al. [21] introduce an explainable fusion model with several deep learning branches to improve diagnostic transparency in cervical cancer detection. The model incorporates saliency maps and class activation methods to offer clinical understanding of classification outcomes. Meza Ramirez C. A. et al. [22] integrate machine learning and spectroscopy to improve cervical cancer screening. Their process involves ensemble learning and spectral feature analysis for reliable and non-invasive diagnosis. Smith K. Khare et al. [23] create an attention-based framework to classify cervical precancer risk from colposcopic images. The explainable attention mechanisms assist in interpreting feature contributions and enhancing trust in AI systems in the clinic.

3. Proposed Methodology

The new model HFFOASVM-MCIC (Hybrid Feature Fusion strategy with Optimized Adaptive SVM for high-performance Multi-class Cervical Image Classification) offers a strong and explainable architecture for multi-class cervical cell image classification. It starts with a careful preprocessing pipeline that improves contrast and minimizes noise within the images, providing uniform input quality.

A hybrid feature combination approach is then applied, mixing Gray-Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradients (HOG), and Local Binary Pattern (LBP) descriptors to extract spatial, textural, and gradient-based details. These features are normalized and dimensionally reduced with PCA to preserve the most discriminative components. The Optimized Adaptive Support Vector Machine (ASVM) serves as the center of the model, and it employs a hybrid kernel based on linear, radial basis, and sigmoid components. The hybrid kernel is optimized via grid search to provide the best decision boundaries for challenging class distributions. The combination of handcrafted features with the tailored ASVM classifier produces excellent classification performance, yielding higher accuracy, precision, recall, and F1-score than conventional techniques. The block diagram of the suggested approach is depicted in figure 1.

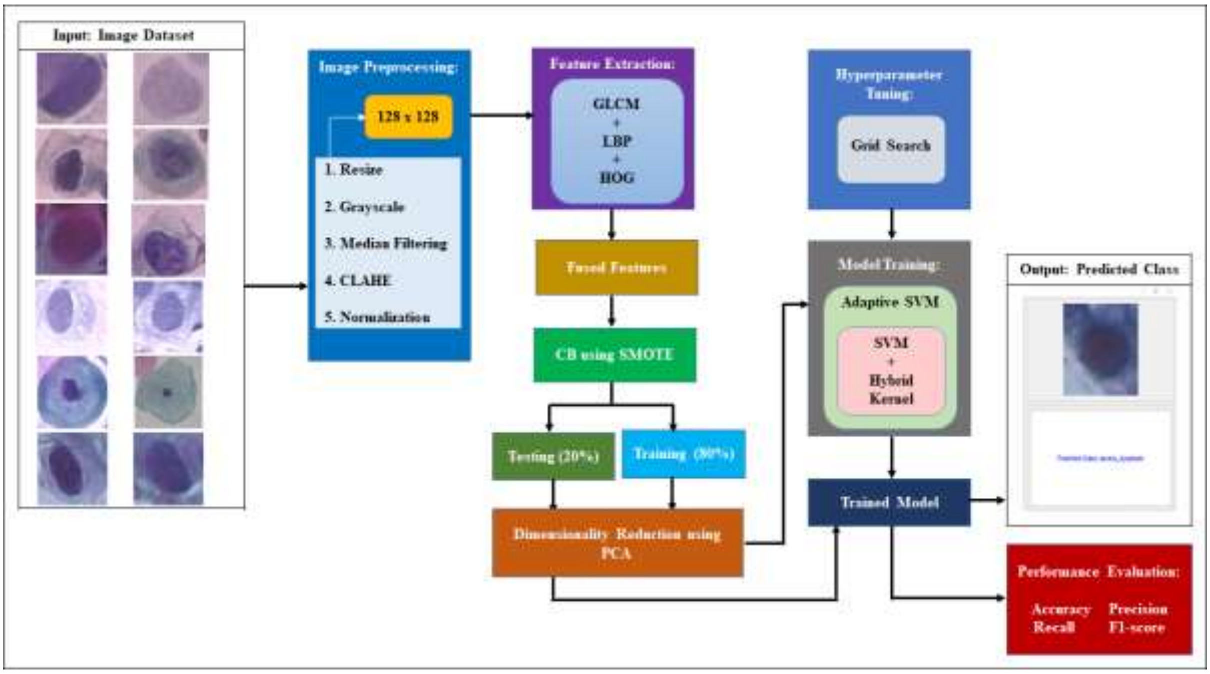


Figure 1. The architecture of the proposed model

3.1 Pre-processing Pipeline for Cervical Image Classification

Preprocessing in medical image classification, especially for cervical histopathological images, is a crucial step to make the input data consistent, free from noise, and optimal for feature extraction and classification. The preprocessing pipeline in this research is developed to enhance the quality and uniformity of cervical images such that they are ready for proper analysis and classification. The following steps form the preprocessing workflow.

Step 1: Grayscale Conversion

Color images often contain redundant information in the context of texture-based classification. Therefore, all RGB images $I_{RGB} \in \mathbb{R}^{H \times W \times 3}$ are converted into grayscale $I_{gray} \in \mathbb{R}^{H \times W}$, as most handcrafted texture features such as GLCM, LBP, and HOG operate on intensity values. The conversion is performed using the luminance method:

$$I_{gray}(x, y) = 0.299 \cdot R(x, y) + 0.587 \cdot G(x, y) + 0.114 \cdot B(x, y) \tag{1}$$

Where R, G, B represent the red, green, and blue color channels, respectively.

Step 2: Noise Reduction via Median Filtering

To reduce salt-and-pepper noise and preserve edges, median filtering is applied to the grayscale image. For each pixel (x, y), the median value of the neighboring pixels in a window $W \times W$ is computed:

$$I_{denoised}(x, y) = \text{median}\{I_{gray}(i, j) | (i, j) \in N(x, y)\} \quad (2)$$

Here, $N(x, y)$ is the local neighborhood around the pixel (x, y). A typical window size used is 3×3.

Step 3: Contrast Enhancement using CLAHE
For enhancing the local contrast and the visibility of cellular structures, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied. Contrary to global histogram equalization, CLAHE applies to small tiles and guards against over-amplifying noise. The process of CLAHE can be described as:

$$I_{enhanced}(x, y) = C(I_{denoised}(x, y)) \quad (3)$$

Where C represents the CLAHE operator that regulates the histogram in contextual regions with a clip limit in order to protect against noise enhancement. It restricts the amplification of the histogram as follows:

$$H_{clip}(i) = \min(H(i), T) \quad (4)$$

$$H_{redistributed}(i) = H_{clip}(i) + \frac{\sum(H(i) - T)}{N} \quad (5)$$

Where $H(i)$ is the original histogram bin, T is the threshold (clip limit), and N is the total number of bins. This ensures uniform contrast distribution.

Step 4: Image Resizing
In order to promote uniformity in extracting features and minimize computational intensity, every amplified image is resized to a fixed size:

$$I_{resized} = \text{resize}(I_{enhanced}, (H', W')) \quad (6)$$

In the implementation, $H' = W' = 128$. This also facilitates standardized input to further stages like feature extraction and classification.

Step 5: Intensity Normalization
After resizing, images are normalized to put pixel intensities within a normalized range, often between 0 and 1, using:

$$I_{norm}(x, y) = \frac{I_{resized}(x, y) - \mu}{\sigma} \quad (7)$$

Here, μ is the mean pixel intensity and σ is the standard deviation. Normalization improves convergence in models and reduces the influence of illumination variability.

3.2 Hybrid Feature Extraction and Fusion Techniques
For enhancing the classification accuracy of cervical histopathological images, discriminative and complementary features need to be extracted that reflect the underlying texture and structure of the tissues. In this work, a hybrid feature extraction method is adopted by combining three of the most recognized handcrafted feature descriptors: Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), and Histogram of Oriented Gradients (HOG). These attributes are subsequently

combined to create an overall description of the input image for classification using the Optimized Adaptive SVM model.

a. Gray Level Co-occurrence Matrix (GLCM)

GLCM is a statistical method that considers the spatial relationship between pixels. It measures how often a pixel with a specific intensity value i occurs in relation to another pixel with intensity j, separated by a distance d and orientation θ. The GLCM $P(i,j;d,\theta)$ is defined as:

$$P(i,j;d,\theta) = \sum_{x=1}^{M}\sum_{y=1}^{N}\begin{cases}1 & if I(x,y)=i \text{ and } I(x+\Delta x,y+\Delta y)=j \\ 0 & otherwise\end{cases} \tag{8}$$

Where $\Delta x = d \cdot cos(\theta)\,, \Delta y = d \cdot sin(\theta)\,, and\ I(x,y)$ denotes the grayscale intensity at pixel location (x,y).

From the GLCM matrix, the following five statistical features are used in this model:

1) Contrast

Contrast is the local intensity difference between a pixel and its neighbor across the whole image. It indicates how different the gray levels of pixels are from one another.

$$Contrast = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2 \cdot P(i,j) \tag{9}$$

2) Correlation

Correlation is a measure of linear dependence between the gray levels of adjacent pixels. It indicates how much the value of one pixel is predictable using its neighbor.

$$Correlation = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)\cdot P(i,j)}{\sigma_i \cdot \sigma_j} \tag{10}$$

Where, $\mu_i\ and\ \mu_j$ are means of rows and columns. $\sigma_i\ and\ \sigma_j$ are standard deviations. A value near 1 or -1 indicates strong correlation; near 0 implies no correlation.

3) Energy

Energy is a measure of uniformity or textural uniformity in an image. It is the summation of squared elements in the GLCM.

$$Energy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}P(i,j)^2 \tag{11}$$

Higher energy values show fewer prominent gray-level transitions, i.e., more uniform or homogenous texture.

4) Homogeneity

Homogeneity is the similarity of the distribution of the elements in the GLCM to the GLCM diagonal. It focuses on the contribution of nearby pixel pairs with minimal intensity differences.

$$Homogeneity = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P(i,j)}{1+|i-j|} \tag{12}$$

Large values of homogeneity reflect a lower contrast or higher similarity of pixels.

5) Dissimilarity

Dissimilarity measures the difference or variability of the gray levels between nearby pixels, as contrast but with a linear weighting.

$$Dissimilarity = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} |i-j| \cdot P(i,j) \tag{13}$$

Contrary to contrast, it rises linearly with gray-level difference and is thus less susceptible to big changes.

b. Local Binary Pattern (LBP)

LBP is an effective texture descriptor that represents the local texture through comparison of each pixel with its neighbors in the neighborhood. For a given pixel I_c, the LBP code is computed as:

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(I_p - I_c) \cdot 2^p \tag{14}$$

Where, P is the number of circularly symmetric neighbor set points, R is the radius of the circle, $s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$, and I_p is the intensity of the p^{th} neighboring pixel.

The result is a binary pattern interpreted as a decimal number. The LBP histogram:

$$H_{LBP}(k) = \sum_{x,y} \delta(LBP(x,y) = k), \;\; k \in [0, 2^P - 1] \tag{15}$$

c. Histogram of Oriented Gradients (HOG)

HOG addresses the edge direction structure in the image. It partitions the image into small cells and calculates the gradient magnitude and direction at every pixel. The gradient can be defined as:

$$G_x = I(x+1, y) - I(x-1, y) \tag{16}$$

$$G_y = I(x, y+1) - I(x, y-1) \tag{17}$$

$$\theta(x,y) = tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{18}$$

$$M(x,y) = \sqrt{G_x^2 + G_y^2} \tag{19}$$

Every cell computes a histogram of gradient orientations weighted by magnitudes. These histograms are concatenated over the image to create the HOG descriptor.

Feature Fusion

Once the feature vectors are extracted separately from GLCM, LBP, and HOG, the fusion method is employed to fuse these features into a unified vector representation. This strategy promotes the learning capacity of the model by capturing varied and complementary information of the image. Let, $f_{GLCM} \in \mathbb{R}^{n_1}$, $f_{LBP} \in \mathbb{R}^{n_2}$, and $f_{HOG} \in \mathbb{R}^{n_3}$, the final fused feature vector is:

$$f_{fused} = [f_{GLCM} \| f_{LBP} \| f_{HOG}] \in \mathbb{R}^{n_1 + n_2 + n_3} \tag{20}$$

Where, || denotes the concatenation operator. To promote scale uniformity between descriptors, standardization is utilized with each feature vector prior to fusion:

$$f' = \frac{f - \mu}{\sigma} \tag{21}$$

Where, μ and σ are the mean and standard deviation of the feature vector f.

This combined feature extraction and fusion approach integrates effectively texture, statistical, and edge-based features, extracting both local and global patterns in cervical histopathology images. The fused vector serves as a strong input to the classification process, enabling the Optimized Adaptive SVM model to acquire strong decision boundaries and consequently improve overall classification performance.

3.3 Classification Process

Classification stage of the proposed model is specifically tailored to produce high discrimination capability for multi-class cervical cell image classification. The steps conform to a step-by-step pipeline: data balancing with SMOTE, train-test split, feature scaling, dimensionality reduction with Principal Component Analysis (PCA), optimized Adaptive SVM classifier with a new hybrid kernel, and hyperparameter tuning with grid search.'

Step 1: Dataset Balancing Using SMOTE

Class imbalance is a typical problem in real-world medical datasets, where some disease classes can be underrepresented. To overcome this, the model applies SMOTE (Synthetic Minority Over-sampling Technique) to create synthetic samples for minority classes. For a sample x_i from the minority class, a new synthetic sample x_{new} is created as:

$$x_{new} = x_i + \lambda \cdot (x_{zi} - x_i) \tag{22}$$

Where, x_{zi} is a randomly selected nearest neighbor of x_i, $\lambda \in [0,1]$ is a random number. This interpolation helps fill the feature space of minority classes, preventing classifier bias.

Step 2: Train-Test Split

In supervised machine learning, it is important to test a model's performance on previously unseen data in order to estimate how well it will generalize on new inputs. Train-Test Split is a basic method for splitting a dataset into two disjoint sets: Training Set and Test Set. Dividing like this ensures that the evaluation metrics represent the model's actual predictive ability, not its ability to memorize the data.

After balancing the dataset, the model splits data into train (80%) and test (20%) sets through stratified splitting to maintain class distribution:

$$Dataset\ D = \{(x_i, y_i)\}_{i=1}^{N},\ D \to D_{train} \cup D_{test}, D_{train} \cap D_{test} = 0 \tag{23}$$

Where, D_{train} is training subset, D_{test} is test subset, and N total number of samples.

Stratified Sampling

In medical data, i.e., in our 6-class cervical image data, classes can be imbalanced. Thus, a stratified split must be done to ensure class distribution is maintained in the training set and the test set. This ensures:

$$\forall_y \in \mathcal{Y},\quad \frac{count_{train}(y)}{|D_{train}|} \approx \frac{count_{test}(y)}{|D_{test}|} \tag{24}$$

Where, $\mathcal{Y}$ is the set of class labels, $count_{train}(y)$ and $count_{test}(y)$ are the number of samples of class y in training and test sets respectively.

Step 3: Feature Scaling

Feature scaling prevents the features from having unequal influence on distance-based learning. The model uses z-score normalization:

$$x_{scaled} = \frac{x-\mu}{\sigma} \quad (25)$$

Where, μ is the mean of the training data, and σ is the standard deviation.

Step 4: Dimensionality Reduction Using PCA
To avoid noise and computational expense, the model uses Principal Component Analysis (PCA). It transforms data to a lower-dimensional subspace with maximum variance maintained. Given centered data $X \in \mathbb{R}^{n \times d}$, PCA finds projection matrix W such that:

$$Z = XW \quad (26)$$

Where, Z is the transformed data in reduced dimension, W contains top k eigenvectors of the covariance matrix $\sum = \frac{1}{n} X^T X$, and the eigenvectors are sorted by decreasing eigenvalues λ, retaining 95% variance.

Step 5: Adaptive SVM Classifier with Hybrid Kernel
Support Vector Machines (SVM) are a type of supervised learning model that seek to establish the ideal decision boundary (hyperplane) between classes by maximizing support vector margins. The decision function for a binary classification issue can be written as:

$$f(x) = sign(w^T x + b) \quad (27)$$

Where, w is the weight vector, b is the bias, and x is the input vector. For non-linearly separable data, SVM uses a kernel function $K(x_i, x_j)$ to map the data into a higher-dimensional space where a linear separation is feasible.

Motivation for Hybrid Kernel
SVMs employ a single kernel in traditional implementations, but every kernel has both advantages and limitations:
Linear: Suitable for linearly separable data
RBF: Suitable for non-linear relationships
Sigmoid: Behaves like neural networks but can be subject to vanishing gradients

To avoid the limitation of a single kernel, the Hybrid Kernel uses several kernels together to capture both linear and non-linear patterns in the data more effectively.

Hybrid Kernel Function
The Hybrid Kernel K_{hybrid} is a weighted combination of three standard kernels:

$$K_{hybrid}(x, x') = \alpha \cdot K_{linear}(x, x') + \beta \cdot K_{sigmoid}(x, x') + (1 - \alpha - \beta) \cdot K_{rbf}(x, x') \quad (28)$$

Where, $\alpha, \beta \in [0,1]$ are weighting parameters, $K_{linear}(x, x') = x^T x'$, $K_{sigmoid}(x, x') = tanh\,(\gamma x^T x' + r)$, $K_{rbf}(x, x') = exp\,(-\gamma \|x - x'\|^2)$.

Such fusion results in a adaptive and flexible decision boundary appropriate for intricate class distributions. The weights $\alpha\ and\ \beta$ are adaptively tuned during model optimization to balance the influence of each component. Adaptive SVM adjusts the kernel parameters dynamically depending on the nature of the dataset.

Step 6: Hyperparameter Tuning via Grid Search
Hyperparameters in machine learning are external settings which cannot be derived from training data but have a tremendous impact on the performance of the model. They need to be established prior to starting the training process. To determine the best-performing Adaptive SVM model, the model executes grid search over important hyperparameters: C - Regularization parameter, γ - RBF kernel width, and α, β - Weights in the hybrid kernel.
Grid Search is a complete search algorithm to discover the best combination of the hyperparameter values which give the maximum performance of a model on a validation set. It performs by: Defining a grid of parameters, training the model with every possible combination of these values, and measuring the model in order to determine the best performing set. Let the set of hyperparameters be:

$$\ominus = \{C, \gamma, \alpha, \beta\} \quad (29)$$

Suppose:

$$C = \{0.1, 1, 10\}, \gamma = \{0.01, 0.1\}, \alpha = \{0.3, 0.5, 0.7\}, \ \beta = \{0.1, 0.3, 0.5\}$$

Then, the grid search will evaluate: Total combinations = $3 \times 2 \times 3 \times 2 = 36$

Each combination is used to train the Adaptive SVM, and its performance $S(\theta)$ is recorded. The optimal configuration is:

$$\theta^* = arg \max_{\theta \in \ominus} S(\theta) \quad (30)$$

In the proposed model, the grid search was used to tune the hybrid kernel weights along with SVM parameters like C and γ. The classifier's final decision function is:

$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i K_{hybrid}(x_i, x) + b\right) \quad (31)$$

Where, α_i is Lagrange multipliers, y_i is Labels, x_i is Support vectors, and b is Bias term.

The Optimized Adaptive SVM (OASVM) presents a strong and efficient solution for image classification applications, especially for challenging datasets such as cervical image classification. Through the use of a hybrid kernel strategy, OASVM effectively deals with combined data complexities and captures both linear and non-linear patterns present in medical images. Its construction promotes noise and class overlap robustness, thus providing improved generalization across different data distributions. The model continues to perform well in high-dimensional feature spaces, particularly after dimensionality reduction by PCA from the composite of various feature descriptors like GLCM, HOG, and LBP. In addition, when integrated with SMOTE oversampling, OASVM solves class imbalance problems effectively, maintaining classification sensitivity for minority classes while enhancing predictive performance overall.

The overall proposed framework is described in the following algorithm.

Algorithm: Hybrid Feature Fusion with Optimized Adaptive SVM for Multi-Class Image Classification (HFFOASVM-MCIC)
Input: Cervical image dataset, trained optimized Adaptive SVM model, Parameters for preprocessing, feature extraction, SMOTE, PCA, and Grid Search. **Output:** Predicted label for test image, Performance metrics and visualization.

Step 1: Load and Preprocess Image
a. Load input image and convert to grayscale.
b. Apply median filtering for noise removal.
c. Perform contrast enhancement using CLAHE.
d. Resize the preprocessed image to a fixed dimension (e.g., 128×128).

Step 2: Hybrid Feature Extraction
a. Extract GLCM features: Contrast, Dissimilarity, Homogeneity, Energy, Correlation.
b. Extract HOG features: Use orientation bins, pixels per cell, and block normalization.
c. Extract LBP features: Compute uniform LBP and histogram.
d. Concatenate all extracted features into a single feature vector.

Step 3: Feature Balancing and Scaling
a. Apply SMOTE to generate synthetic samples for minority classes.
b. Apply random undersampling to balance the dataset.
c. Normalize feature values using StandardScaler.

Step 4: Feature Selection and Dimensionality Reduction
a. Use ANOVA F-test (SelectKBest) to retain top-k features.
b. Apply PCA to reduce feature dimensionality while preserving 95% variance.

Step 5: Optimized Adaptive SVM Classifier
a. Define hybrid kernel K(x, x') = α*K_linear + β*K_sigmoid + (1 - α - β)*K_rbf.
b. Train Adaptive SVM using the hybrid kernel.
c. Tune hyperparameters C, γ, α, β using Grid Search.

Step 6: Classification and Evaluation
a. Predict test image class label using trained Adaptive SVM model.
b. Compute metrics: Accuracy, Precision, Recall, F1-score.
c. Display confusion matrix and ROC curve.

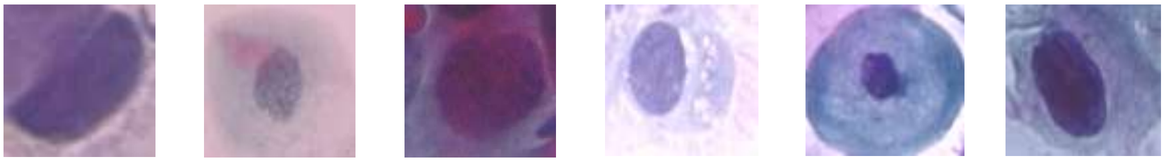
4. Results and Discussion

The HFFOASVM-MCIC model proposed here is constructed and deployed based on Python's solid machine learning library and tool ecosystem. In order to stringently test its performance, the model is trained and tested on a publicly available cervical image dataset [24] that comprises 897 images scattered over six clearly differentiated disease classes. The data covers a broad spectrum of cervical lesions and imaging paradigms and provides an extensive and demanding test bed for multi-class model validation. To test rigorously with experimental validation, the dataset was split categorically into a training and a testing subset in 80:20 ratios. The performance of the model was checked on generally utilized measures of performance such as accuracy, precision, recall, and F1-score. A comprehensive description of the dataset such as per-class images and their corresponding labels is given in Table 1.

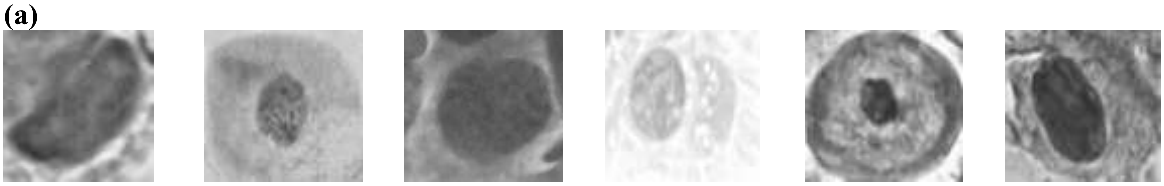
Table 1: Detail on Dataset

Classes	**No. of Images**
carcinoma_in_situ	150
light_dysplastic	182
moderate_dysplastic	146
normal_columnar	112
normal_intermediat	110
severe_dysplastic	197
Total Images	**897**

Figure 2 (a) depicts the sample original images of six different classes and its pre-processed ones are shown in Figure 2 (b).



(a)



(b)

Figure 2. (a) Original Images (b) Pre-processed Images

Figures 3 to 8 show the GUI designed for cervical disease classification based on the suggested HFFOASVM-MCIC model. Such an easy-to-use and interactive GUI helps end-users (clinicians) select and classify test images into their corresponding disease categories easily. As illustrated in Figure 3, the central interface is made up of five main buttons Load Image, Preprocess, Extract Features, Classify, and Exit, placed on the left panel, with exclusive display areas on the right for the chosen image, the preprocessed image, and the classifying result. After clicking on the Load Image button, a file dialog is invoked, with which users can navigate and choose a test image on their system. After a selected image is shown in the allocated space, the Load Image button is disabled and the Preprocess button is enabled to direct the user to the next level.

When the Preprocess button is clicked, a series of preprocessing transformations are applied to the processed image, such as resizing, contrast stretching, noise removal, and normalization. The preprocessed image resulting from these operations is then shown, and the Preprocess button is disabled and the Extract Features button is enabled. After the Extract Features button is pressed, the system extracts a fused feature vector with the help of the GLCM, HOG, and LBP methods. After that, it gives a message of confirmation to inform the user. Lastly, the Classify button click loads the pre-trained Optimized Adaptive SVM (OASVM) model for processing the features that were extracted. The model classifies the extracted features and predicts the respective disease class. The predicted class label is later presented in the result window. Such a systematic and step-by-step interface design improves the user experience to the extent that the process of classification becomes easy, user-friendly, and diagnostically accurate.

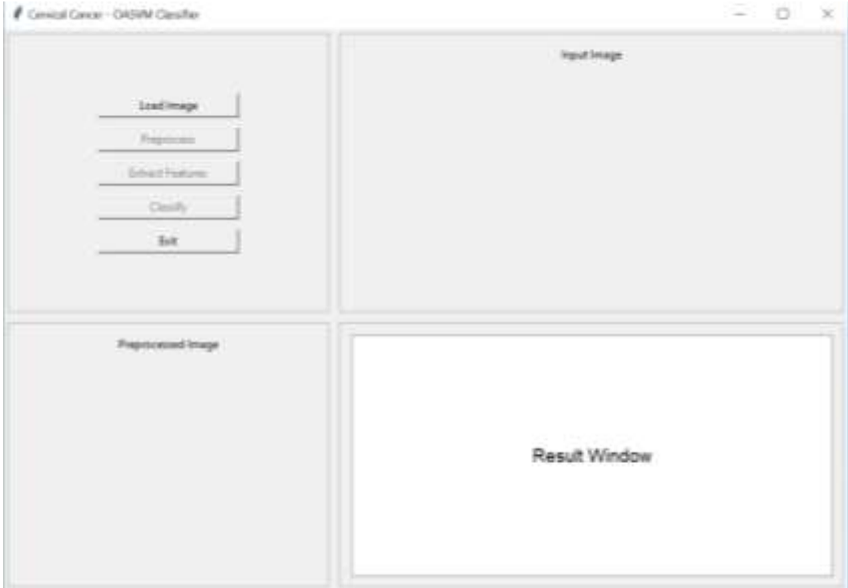


Figure 3. The GUI design for HFFOASVM-MCIC Framework

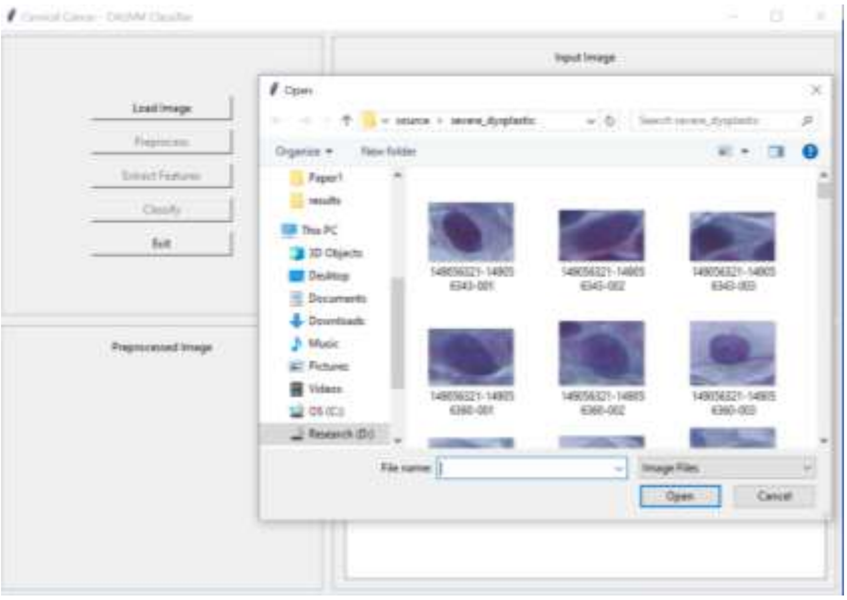


Figure 4. The GUI shows a dialog box to select an image

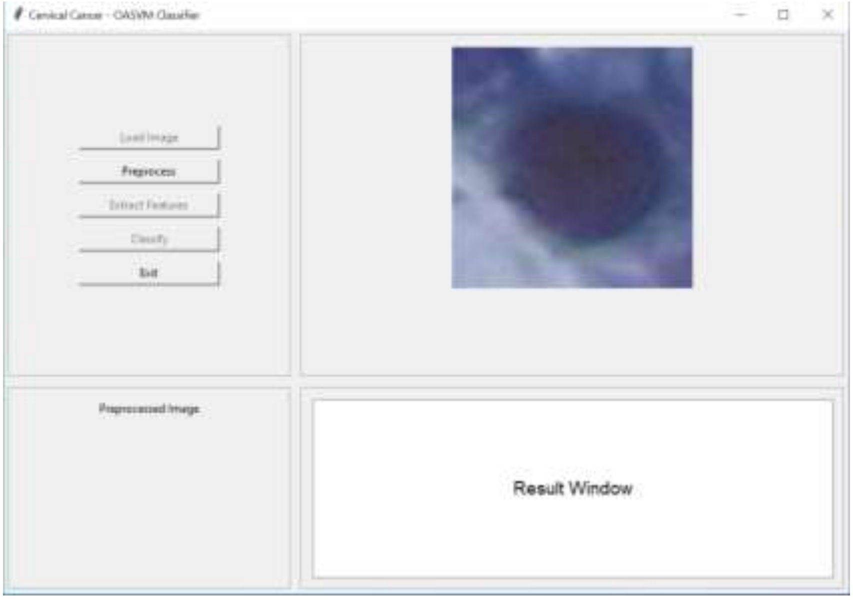


Figure 5. The GUI shows the loaded original image

Figure 6. The GUI displays the original and pre-processed images

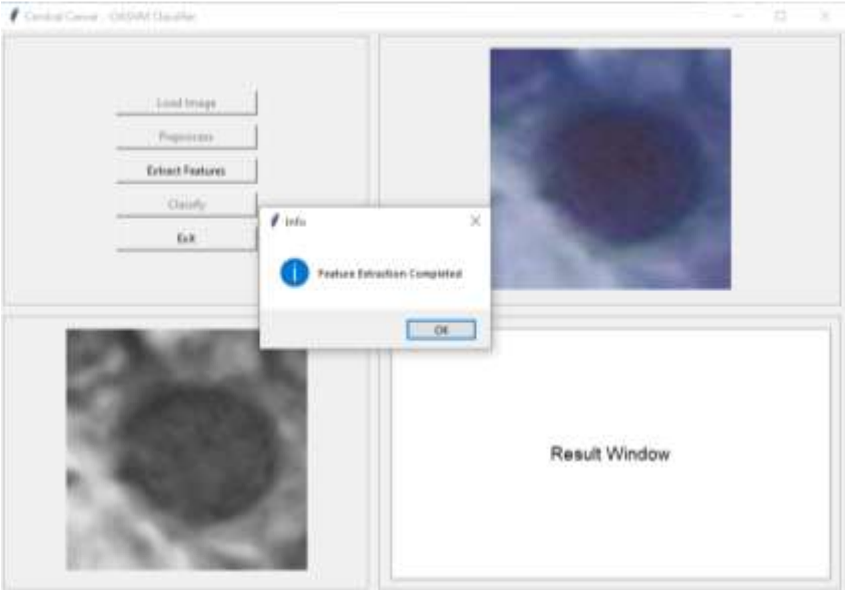
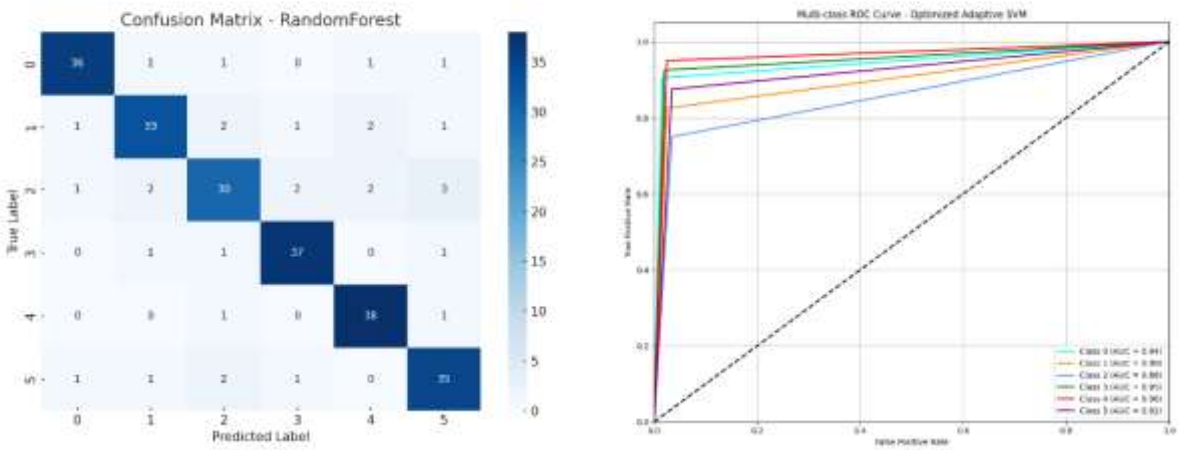


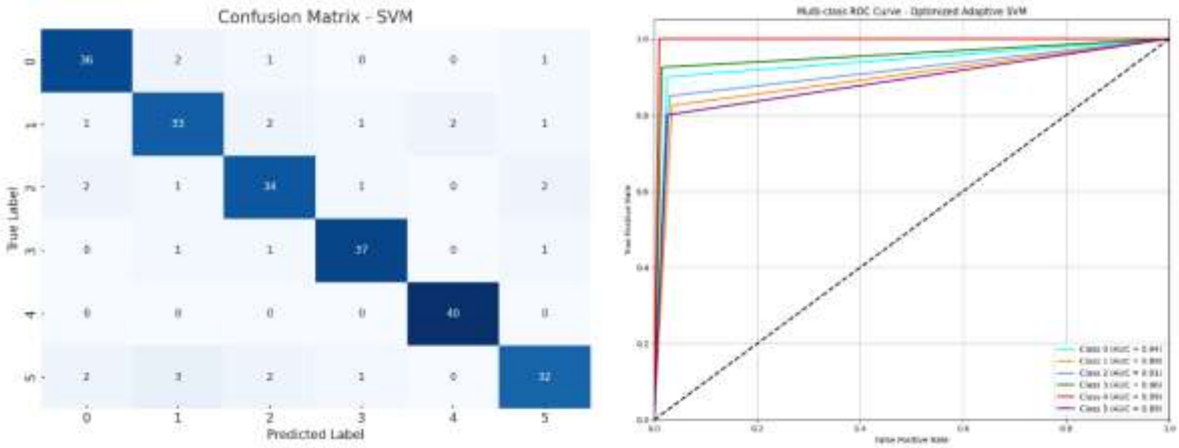
Figure 7. The GUI displays the confirmation of the feature extraction message

Figure 8. The GUI displays the predicted label in the result window

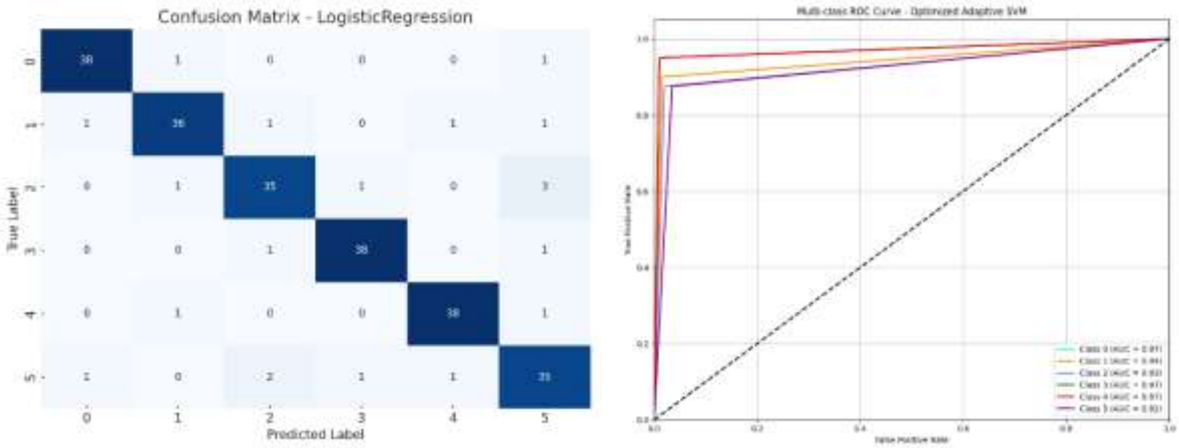
Figure 9 shows the classification performance achieved by the proposed HFFOASVM-MCIC framework and a number of other benchmark models using the test dataset. Figure 9(a) gives the confusion matrix and Receiver Operating Characteristic (ROC) plots for each class of diseases as produced by the Random Forest (RF) classifier. Figure 9(b) indicates the results obtained using the Support Vector Machine (SVM) model, whereas Figure 9(c) indicates the outcome of the Logistic Regression (LR) model. Lastly, Figure 9(d) identifies the outputs generated by the new HFFOASVM-MCIC model. Uniform distribution of well-classified samples over all disease classes in Figure 9(d) illustrates the uniform and robust nature of the new framework.


Confusion Matrix - RandomForest
True Label
Predicted Label
Multi-class ROC Curve - Optimized Adaptive SVM

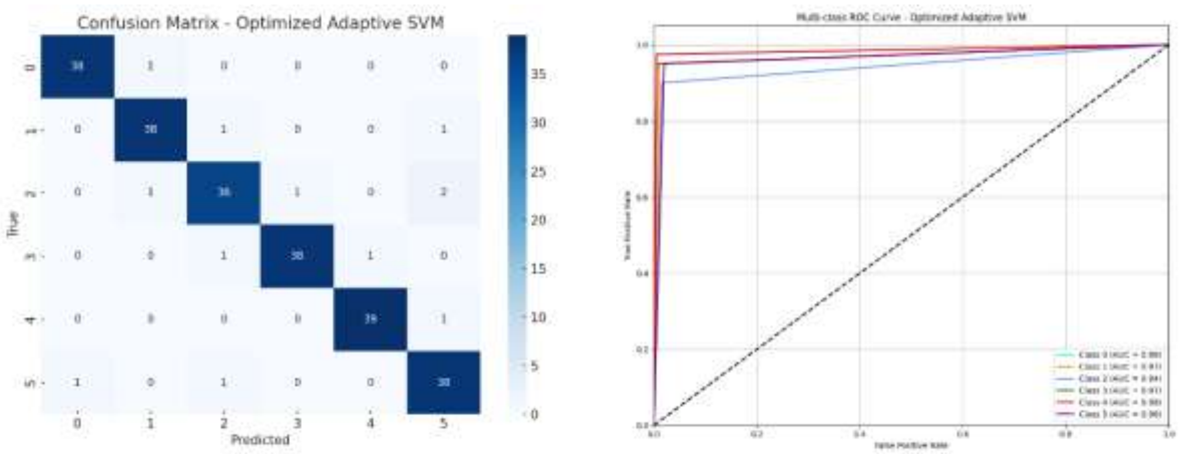
(a)


Confusion Matrix - SVM
True Label
Predicted Label
Multi-class ROC Curve - Optimized Adaptive SVM

(b)


Confusion Matrix - LogisticRegression
True Label
Predicted Label
Multi-class ROC Curve - Optimized Adaptive SVM

(c)



(d)

Figure 9. Confusion Matrix and ROC Curve analysis of HFFOASVM-MCIC approach with existing models

Table 2 and Figure 10 show the results of a thorough comparative study, highlighting the better performance of the new HFFOASVM-MCIC model with respect to some state-of-the-art methods. Experimental results indicate that traditional models like RF and SVM registered relatively lower classification accuracies of 84.23% and 90.14%, respectively. The LR model performed better, registering 90.98% accuracy, which indicates its proficiency in dealing with intricate visual patterns. But the given HFFOASVM-MCIC framework outperformed all the baseline models by a huge margin, yielding a very high classification accuracy of 95.20%. This significant enhancement demonstrates the efficacy of the hybrid feature fusion method and the optimized adaptive SVM classifier used under the HFFOASVM-MCIC architecture. The comparative assessment unmistakably puts HFFOASVM-MCIC forward as a very accurate, stable, and reliable model for cervical disease classification, further affirming its potential as an advanced solution for actual medical diagnostic applications.

Table 2. Result analysis of HFFOASVM-MCIC model with existing models

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
RF	84.23	82.08	84.03	81.04
SVM	90.14	89.19	89.87	86.02
LR	90.98	88.88	90.78	89.50
OASVM	95.20	93.41	95.04	94.02

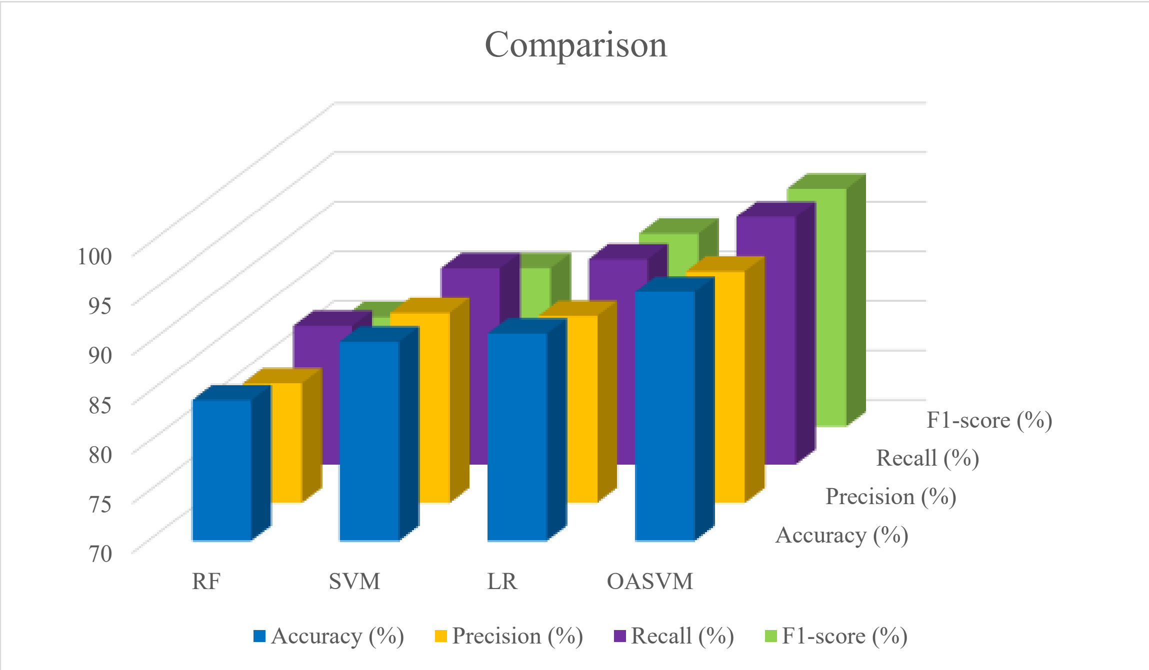


Figure 10. Results analysis of HFFOASVM-MCIC approach with existing techniques

5. Conclusion

A new hybrid model HFFOASVM-MCIC is introduced in this research work to improve the accuracy and trustworthiness of cervical disease categorization. Overcoming major challenges like high intra-class similarity, low inter-class variability, and imbalanced datasets, the proposed model combines an efficient image pre-processing pipeline, a stable hybrid mechanism for feature extraction, and an optimally adjusted adaptive SVM classifier. The pre-processing module normalizes cervical images through improving contrast, noise removal, and intensity normalization to enhance the quality and uniformity of the data. The hybrid feature extraction approach integrates GLCM, HOG, and LBP for extracting textural and structural features from cervical images. This integration greatly enriches the feature space for better discrimination between classes of diseases. To further improve classification performance, feature vectors are reduced in dimension via PCA, and class imbalance is dealt with effectively by the SMOTE. The Adaptive SVM is the central classifier, using a hybrid kernel that includes linear, radial basis function, and sigmoid components, the weights for which are optimized to create a dynamically balanced kernel. Hyperparameter tuning via grid search ensures the model is optimized to exactly match the underlying data distribution.

Experimental findings on a benchmark cervical image dataset of six disease classes prove the superiority of the HFFOASVM-MCIC model. It obtained a classification accuracy of 95.20%, surpassing traditional classifiers like Random Forest, SVM, and Logistic Regression. Moreover, the model exhibits steady performance across all classes, as indicated by high precision, recall, and F1-scores, and balanced confusion matrices and ROC curves. The effective combination of state-of-the-art pre-processing, hybrid feature learning, and kernel optimization in this study makes HFFOASVM-MCIC an effective medical image analysis tool. In the future, this framework can be expanded to larger and more heterogeneous datasets, and converted for real-time use in clinical decision support systems for early cervical cancer detection.

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