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Article Title: **An Efficient Cervical Cancer Prediction Using Chicken Swarm Optimized Ann Classifier**

An Efficient Cervical Cancer Prediction Using Chicken Swarm Optimized ANN Classifier

S. Karthick

Associate Professor, Department of Electronics and Communication Engineering, Erode Sengunthar Engineering, College, Erode, Tamilnadu, India. researchkarthick@gmail.com

ABSTRACT

Cervical cancer remains a significant global health challenge, ranking as a leading cause of cancer-related deaths among women. This research addresses the need for improved detection methods by leveraging advanced image processing techniques. Implement Adaptive Median Filtering (AMF) for effective noise reduction while preserving critical details in cervical images, enhancing overall image quality. Utilizing K-means clustering for segmentation, accurately isolate regions of interest, and Local Binary Patterns (LBP) for feature extraction enable improved differentiation between normal and cancerous tissues. Additionally, the integration of the Chicken Swarm Optimized algorithm with Artificial Neural Networks (CSOANN) significantly enhances classification accuracy, facilitating earlier detection of cervical cancer. These methodologies not only improve diagnostic accuracy but also contribute to better patient outcomes and more effective screening strategies, ultimately advancing cervical cancer management.

Keywords: Cervical cancer, Adaptive Median Filtering, K-means cluster, Local Binary Patterns, Chicken Swarm Optimization algorithm, Artificial Neural Networks.

1 Introduction

Cervical cancer is a widespread gynecological disease worldwide, representing a major threat to women's health. It is leading cause of cancer-related deaths among women worldwide, underscoring the importance of awareness and regular screening. It is primarily caused by persistent infection with high-risk types of Human Papillomavirus (HPV). One of the primary methods for detecting cervical cancer is cervical cytology, commonly referred to as the smear test and HPV test. These screening tool is instrumental in identifying cancer at earlier stages, which significantly lower mortality rates. Early detection is crucial, as it enhances the chances of survival through various stages of the disease. Successful prevention primarily relies on screening the transformation zones of the cervix, the narrow channel that connects the uterus. Regular medical check-ups are essential for early detection and effective intervention [1-2].

At the early stage, the Thinprep Cytology Test (TCT) and HPV testing are the most effective methods for cervical screening. The HPV test specifically identifies the presence of high-risk viruses that lead to cervical lesions or cancer. Meanwhile, TCT detects abnormal changes in cervical cells, which are significant indicators of potential cervical cancer. Access these screenings is crucial for effective prevention, especially in populations with limited awareness

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and education about the disease. Transitioning to advance imaging techniques, such as colposcopy and MRI, provides a more detailed view of cervical cancer [3-4]. Image processing technologies enhance diagnostic accuracy, allowing for better visualization of abnormalities and reducing misleading cytological results. Image processing involves several key types, including preprocessing, segmentation, feature extraction, and classification.

Preprocessing image filtering technique is essential for removing noise and smoothing images to enhance their quality for analysis. For instance, mean filtering is straightforward and effectiveness in reducing noise, making it ideal for real-time applications and rapid processing. However, it affect a potential for blurring or losing fine details. Median filtering effectively eliminate salt-and-pepper noise without blurring edges, but it sometimes lead to the loss of fine details in the image. Gaussian blur smooths the image by reducing high-frequency components, which create a more visually appealing result. However, it also obscure important features and edges, potentially affecting the accuracy of subsequent analyses [5-7]. To address these challenges, preprocessing image filtering explore the AMF used in cervical cancer image analysis to effectively reduce noise while preserving important structural details, which is crucial for accurate diagnosis. This technique is particularly beneficial in preparing images for further analysis, such as segmentation, feature extraction and classification in Machine Learning (ML) models.

Segmentation involves dividing an input sample into distinct regions to isolate the Region of Interest (ROI) while removing the background. Threshold solutions in image segmentation, achieving a favorable balance between exploration and exploitation. Additionally, these techniques demonstrate robustness and improved optimization performance, leading to superior segmentation outcomes. However, the segmentation targets is highly sensitive to threshold selection, making it challenging to achieve robust results in practical applications [8-9]. Over this limitations, segmentation explore K-means clustering that offer high clinical utility and aiding medical specialists in diagnosis of cervical cancer by segmenting input image in the ROI. K-means segmentation requires several operations, including area filtering and template construction, to obtain the segmented cervical region effectively.

Next step, feature extraction utilizes texture features after segmenting and processing images. Techniques such as the Gray Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transform (DWT) etc. The GLCM generates metrics including energy, correlation, homogeneity, entropy, and contrast, but its computational intensive with large datasets, impacting the significance of the features. Conversely, DWT derived from the image's decomposition using low-pass and high-pass filters. However DWT result in a loss of information during the decomposition process, potentially influencing the relevance of the extracted features [10-11]. To tackle this issue, feature extraction method implement LBP analysis of effectively highlights texture variations in cervical cancer images, enhancing differentiation between benign and malignant tissues. Additionally, integrating LBP with ML

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techniques further refine predictive models, contributing to more effective screening strategies in cervical cancer prevention.

Finally, ML classification technique in cervical image processing involves categorizing images based on features to identify conditions. Classification methods such as K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Generative Adversarial Networks (GANs) etc. KNN for cervical cancer classification is simplicity and ease of implementation, allowing for straightforward interpretation of results and quick adaptation to different datasets without extensive parameter tuning. Nevertheless, using KNN for cervical cancer classification is sensitivity and the number of features increases, the algorithm struggle to potentially leading to decreased accuracy and higher computational costs [12]. SVM ability to handle high-dimensional data effectively, making them suitable for analyzing complex datasets in cervical cancer. It provide robust classification results even with a limited amount of training data. However, SVM is sensitive to the choice of kernel and hyper parameters, which require extensive tuning. It also struggle with imbalanced datasets, leading to suboptimal performance in identifying rare cases. GANs offer generating synthetic data, which enhance training datasets, especially in cases of limited available data for cervical cancer that capability improve the robustness and help mitigate overfitting. However, GANs are complex to train and require substantial computational resources [13-14]. Advanced classification techniques Chicken Swarm Optimized (CSO) algorithm applied with Artificial Neural Network (ANN) enhances their ability to accurately classify and predict cancerous lesions from medical data. This approach enhances optimization, allowing the model to achieve better accuracy in identifying cancerous lesions. The CSO-ANN framework provides a robust, adaptable solution that outperforms traditional methods in diagnostic accuracy and efficiency. In this model improving diagnostic accuracy, potentially leading to earlier detection and better patient outcomes in cervical cancer management.

This research enhances cervical cancer detection through advanced image processing techniques, particularly AMF, which preserves crucial details while reducing noise. By utilizing K-means clustering for segmentation and LBP for feature extraction, in this study improves the identification of normal versus cancerous tissues, resulting in more accurate diagnoses. Furthermore, the integration of the CSOANN significantly boosts classification accuracy, facilitating earlier detection and improved patient outcomes in cervical cancer management, as discussed in the subsequent modelling section.

2 Proposed System Description and Modeling

Block Diagram

The processing of cervical cancer images plays a crucial role in early detection and diagnosis. The workflow typically begins with preprocessing techniques to enhance image quality, followed by segmentation, feature extraction, and classification. Figure 1 represents the block

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diagram of proposed system that illustrate the performance of image processing in cervical cancer.

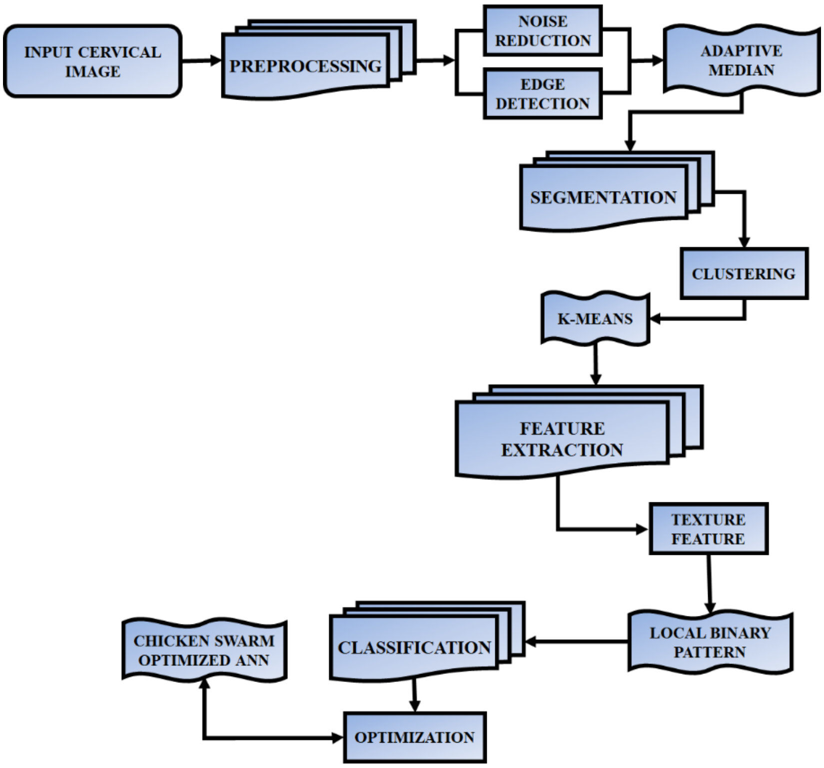

Figure 1: *Block diagram of proposed system.*

The image processing workflow for cervical cancer diagnosis involves several key steps. First, AMF is applied to the input cervical images that technique effectively reduces noise while preserving important edges, enhancing the clarity of the images for subsequent analysis. Following preprocessing, the next step is segmentation using the K-means clustering algorithm. K-means groups pixels into clusters based on their intensity values, allowing for the identification of different regions within the image, such as tissues or potential abnormalities. This step is vital for isolating areas of interest that indicate cervical cancer. Once segmentation is complete, features are extracted using the LBP method. LBP captures texture information by comparing pixel values with their neighbors, generating a binary pattern that reflects the local structure. This feature extraction is crucial for distinguishing between healthy and abnormal tissues. Finally, the extracted features are classified using a CSOANN that classification technique utilizes optimization algorithms inspired by the behavior of chickens to enhance the ANN's performance, ultimately improving the accuracy of the diagnosis. The entire process comprising preprocessing, segmentation, feature extraction, and classification results in a robust system for the detection of cervical cancer. By enhancing image quality and accurately identifying abnormal regions, this workflow aids in timely and effective diagnosis, which is essential for better patient outcomes.

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2.1 Prepeocessing Based Adaptive Median Filter

Cervical cancer diagnosis, preprocessing plays a crucial role in preparing input images for accurate analysis. By applying an AMF to the cervical cell images, effectively reduce noise, particularly salt-and-pepper noise, while preserving important structural details. This filter operates by dynamically adjusting its window size based on local pixel characteristics, ensuring value calculated from each pixel. This adaptability allows it to effectively target and remove high-density impulse noise without significantly blurring the image. The AMF effectively reduces noise while preserving the integrity of the underlying image structure. It is enhances the overall image quality, allowing for clearer visualization of cellular structures and abnormalities. The AMF method functions on two tiers, the A layer and the B layer. The procedure is summarized as follows:

A layer: If $f_{min} < f_{med} < f_{max}$, proceed to B layer; in other ways, increase the size of the windowA_{ij}. If the current size of A_{ij} is less than A_{max} repeat the A layer, whether retain thef_{ij}.

B layer: If f_{min}<f_{ij}<f_{max}, then maintain the f_{ij} is unchanged; otherwise set f_{ij} =f_{med}.

The A layer determines whether f_{med} represents an impulse noise, while the B layer access if f_{ij} is noise. When neither f_{med} nor f_{ij} is classified as impulse noise, the algorithm preserves the original pixel value f_{ij} rather than using the central value of the surrounding area as the result to prevent excessive loss of important information. The method for detecting and recognizing noise relies on f_{min} and f_{max} . Then observing to $f_{min} < f_{ij} < f_{max}$ even if $f_{ij}$is a noise value. When both f_{ij} and $f_{med}$are not impulse noise output of f_{ij}.

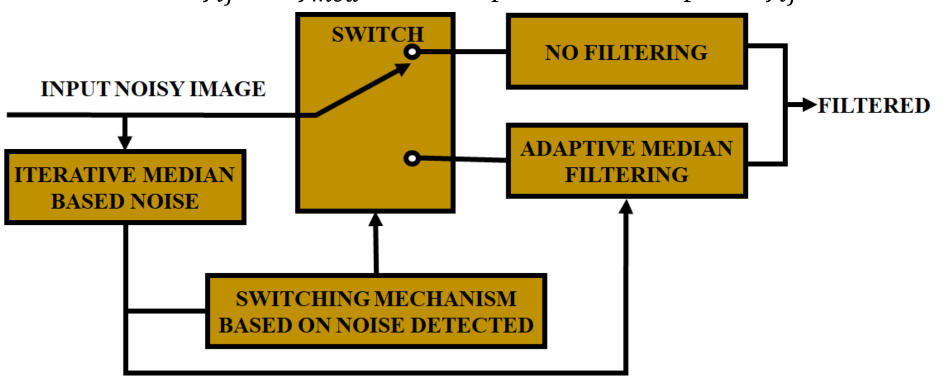

Figure 2: *Architecture of AMF*

Figure 2 represents the architecture of AMF, which illustrates the process of dynamically adjusting the filtering operation based on the image. This approach enables the filter to effectively remove noise while preserving important details, such as edges and textures. This preprocessing step is essential for subsequent segmentation and classification tasks, ultimately contributing to more reliable diagnostic outcomes. This is more selective a filter, preserving

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edges and other high-frequency parts of an image. After preprocessing the images, proceed to segmentation to accurately identify and classify the different features.

2.2 Segmentation Based K-Means Algorithm

K-means segmentation is increasingly utilized in the analysis of cervical cancer images, providing crucial support in the diagnosis and treatment planning processes. This technique effectively categorizes pixel data from medical images, such as histopathological slides or cervical scans, into distinct clusters based on color and texture features, allowing for the identification of abnormal cells and tissues. In cervical cancer research, K-means segmentation is particularly useful for analyzing images, where it differentiate between normal, dysplastic, and cancerous cells. The input images in the preprocessed RGB color format transformed into the HSV color space, and the V component isolated using the K-means clustering method. Subsequently, an area filter applied to refine the edges for effective segmentation of the cervical region. Finally, transformed the RGB input image into the HSV color space.

$$V = max\ (R, G, B) \tag{1}$$

$$S = \begin{cases} \frac{V - min(R,G,B)}{V}, V \neq 0 \\ 0. otherwise \end{cases} \tag{2}$$

$$H = \begin{cases} 60 * (G - B)/\left(V - min(R, G, B)\right), V = R \\ 120 + 60 * (B - R)/\left(V - min(R, G, B)\right), V = G \\ 240 + 60 * (R - G)/\left(V - min(R, G, B)\right), V = B \end{cases} \tag{3}$$

The K-means clustering is a quick and straightforward clustering technique that separates the data points into K categories. The K-means segments the pixels in the input image into K cluster centers. The process involves determining the average value of the data points within each cluster to establish new cluster centers. When there is no change in the positions of two neighboring clusters, it indicates that the adjustments for the samples are complete, and the clustering criterion function reached convergence. The hypothesis is defined as,

$$P = \{p_{i,j}\}_{i=1,j=1}^{N,M} \tag{4}$$

Where, p denotes a pixel, and N and M represents the number of rows and columns, respectively. Each pixel $P_i = (h_i, s_i, v_i)$ is expressed in the HSV color space after conversion. The set $\{\hat{P}_j\}_{j=1}^{K}$ includes the pixels intended for clustering, where$\hat{P}_j = (h_i, s_i, v_i)$.

$$D(K) = \sum_{i=1}^{L} min\left(p_i - \hat{p}_j\right)^2 \tag{5}$$

Equation (5) represents the minimum Euclidean distance between the calculated pixel values and the cluster centers within the K-means algorithm. As the value of K varies, pixels that closely resemble the cluster center are progressively grouped together.

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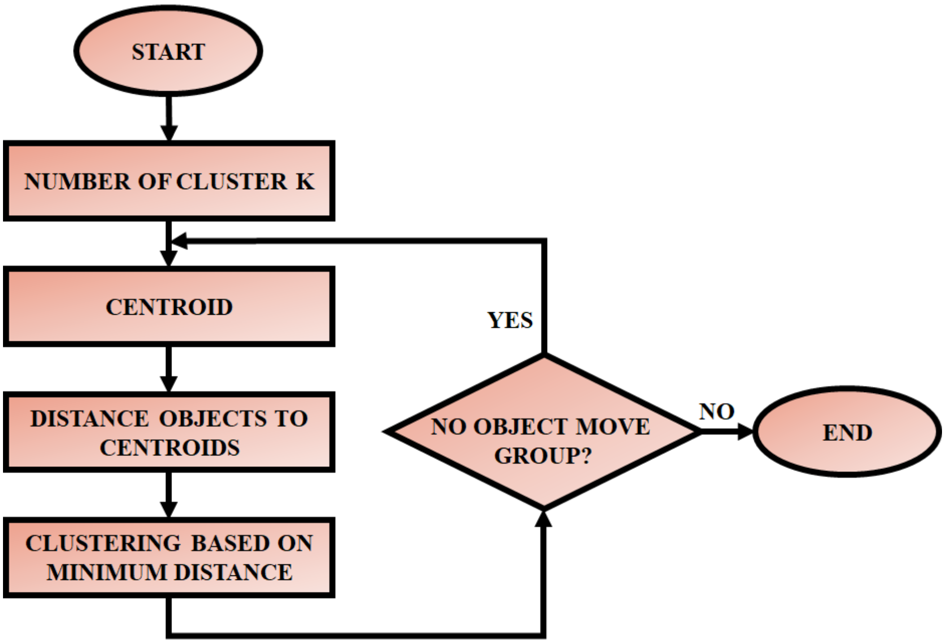

Figure 3: *Flowchart of k means clustering algorithm.*

Figure 3 represents the flowchart of the k-means clustering algorithm that outlines the step-by-step process for partitioning a dataset into distinct clusters. After successfully applying the K-means algorithm for segmentation, which grouped the data into distinct clusters based on similarity, now move on to feature extraction to identify the key characteristics that define each cluster and enhance analysis.

2.3 Feature Extraction Based Local Binary Pattern

Feature extraction is a critical step following the segmentation of images, particularly in the context of texture analysis. LBP is a key texture-based method used for extracting informative features from single cell images in cervical cancer detection. LBP works by analyzing the local patterns of pixel intensity around each pixel, effectively capturing textural characteristics that highlight the contours of the nucleus and cytoplasm. This feature extraction is crucial for distinguishing between normal and cancerous cells. LBP, the texture of the image using high-order derivatives to classify cells as normal or cancerous. LBP is a straightforward yet highly effective texture operator that assigns labels to the pixels of an image by thresholding the surrounding pixels of each central pixel. This process treats the outcomes as a binary number and strong discriminative capability and ease of computation. The LBP method utilizes a 3x3 mask window over the original image, comparing the central pixel to its neighbors. The results are stored in binary format: if a neighboring pixel's value is greater than or equal to that of the central pixel, it is encoded as 1; otherwise, it is encoded as 0. The LBP, characterized by a specified radius R and number of neighboring pixels P, is defined as follows.

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$$LBP_{P,R} = \sum_{p=1}^{P} 2^{p-1} \times f_1(g_p - g_c), \quad f_1(x) = \begin{cases} 1 & x \geq 0 \\ 0 & else \end{cases} \tag{6}$$

Where gray value of the central pixel represents g_c and value of gray neighboring pixels denotes g_p.

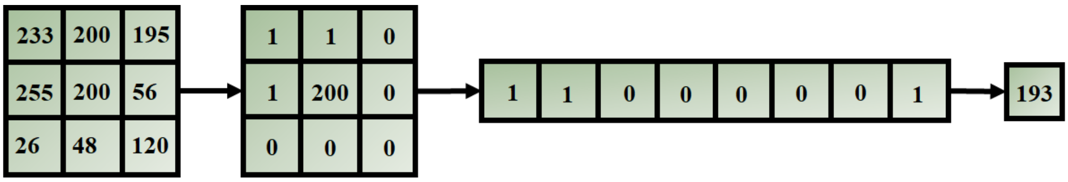

Figure 4: *Texture unit of LBP*.

Figure 4 represents the texture unit of LBP, illustrating captures and encodes local texture information in an image. The integration LBP features proven to enhance the overall accuracy of cervical cancer detection, demonstrating its effectiveness in improving diagnostic outcomes. Once the feature extraction process is complete, the image data is then processed using a classification technique to categorize the cells as either benign or malignant for cervical cancer diagnosis.

2.4 Classification Based Chicken Swarm Optimized Artificial Neural Network

CSO is an innovative approach utilized in data mining for feature selection, enhancing the classification of medical data. The CSO algorithm, inspired by natural behaviors, effectively applied to classification, particularly for predicting cervical cancer. In this research, CSO is combined with ANN to form a hybrid method known as CSOANN. This algorithm has demonstrated its capability to achieve remarkable optimization results. In CSO utilized with ANN cervical Cancer risk factors dataset to enhance classify and identify the likelihood of cancer at an early stage. This hybrid approach aims to identify the most relevant feature subsets related to a target class, thereby improving the overall performance of the classifier. CSOANN is an advanced method employed for the classification of cervical cancer data, enhancing the accuracy and efficiency of diagnosis. CSOANN operates as a back propagation network, where simple processing units collaborate to generate outputs. The adaptability of CSOANN in configuring neuron weights allows for the formation of interconnected neurons, each serving as a fundamental unit in processing information and driving the model's performance.

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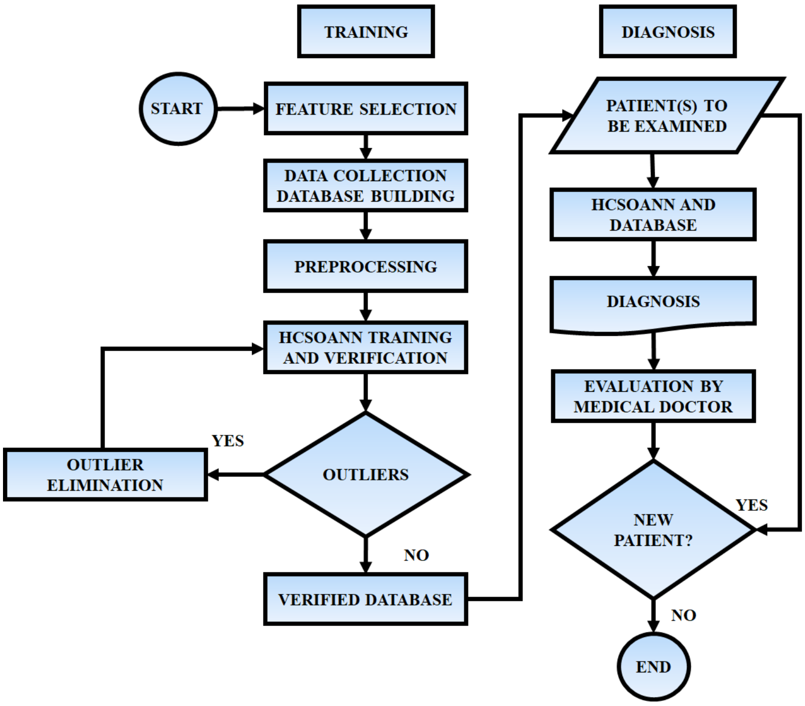

Figure 5: *Process flow of CSOANN.*

Figure5 represents the process flow of the CSOANN, illustrating the algorithm trained and verified the image processing that evaluate by the medical doctor. CSOANN plays a significant role in decision-making within the medical field, enhancing the reliability of healthcare delivery to the general population. It is capable of identifying unusual conditions, filling gaps in clinicians' knowledge regarding disease predictions, even in specialized areas. The effectiveness of the CSOANN model is availability of extensive patient data in electronic formats, enabling accurate detection of variations in physiological parameters, a critical indicator in cervical cancer disease diagnosis. The mathematical framework of CSOA relevant to study is represented as follows,

$$A_{f,g}^{q+1} = A_{f,g}^{q}\left(1 + rand(0, \alpha^2)\right) \tag{7}$$

$$\alpha^2 = \begin{cases} 1, \\ exp\left(\frac{(b_c - b_f)}{|b_f| + \varepsilon}\right) \end{cases} \tag{8}$$

In a standard Gaussian distribution, the mean is represented by 0, while α^2signifies the variance. The symbol ε denotes a small value that not treated as zero during division. CSOANN used to detect and prevent the early stage of cervical cancer and very fast optimization for classification. This hybrid method achieve a better optimization results and accuracy in terms of performance as cervical cancer.

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3 Result and Discussion

This work presents the images for training and testing of cervical cancer detection system using advanced image processing techniques. Additionally, CSOANN based classification for cervical cancer model accurately identify different types of cervix lesions. Furthermore, this work implemented by python software tool for cervical cancer detection and the obtained results are discussed below.

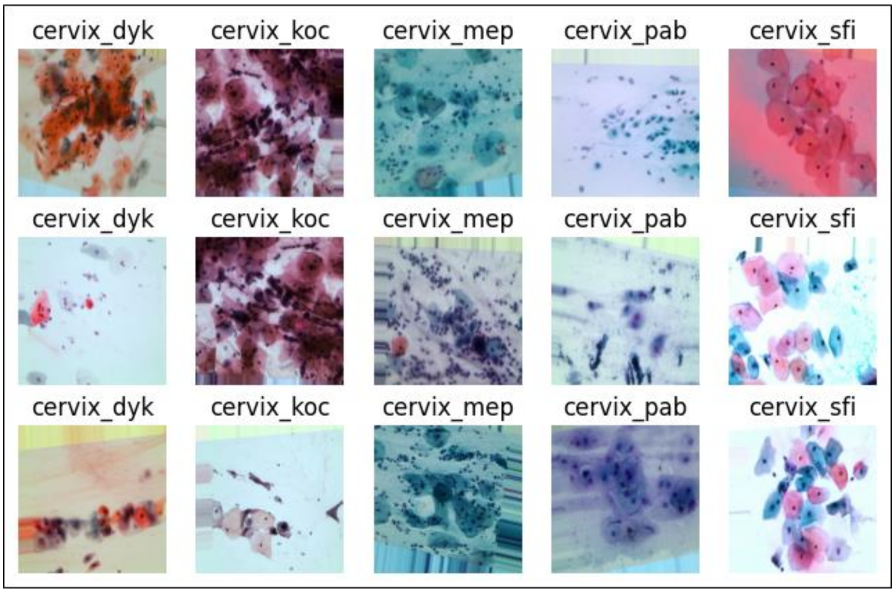

Figure 6: *Dataset of cervical cancer image.*

Figure 6 represents the dataset of cervical cancer images that illustrating the samples in various types of cervix tissue. This dataset highlights the distinction between the various types the cervical cancer lesions which are crucial for accurate diagnosis and research in cervical cancer.

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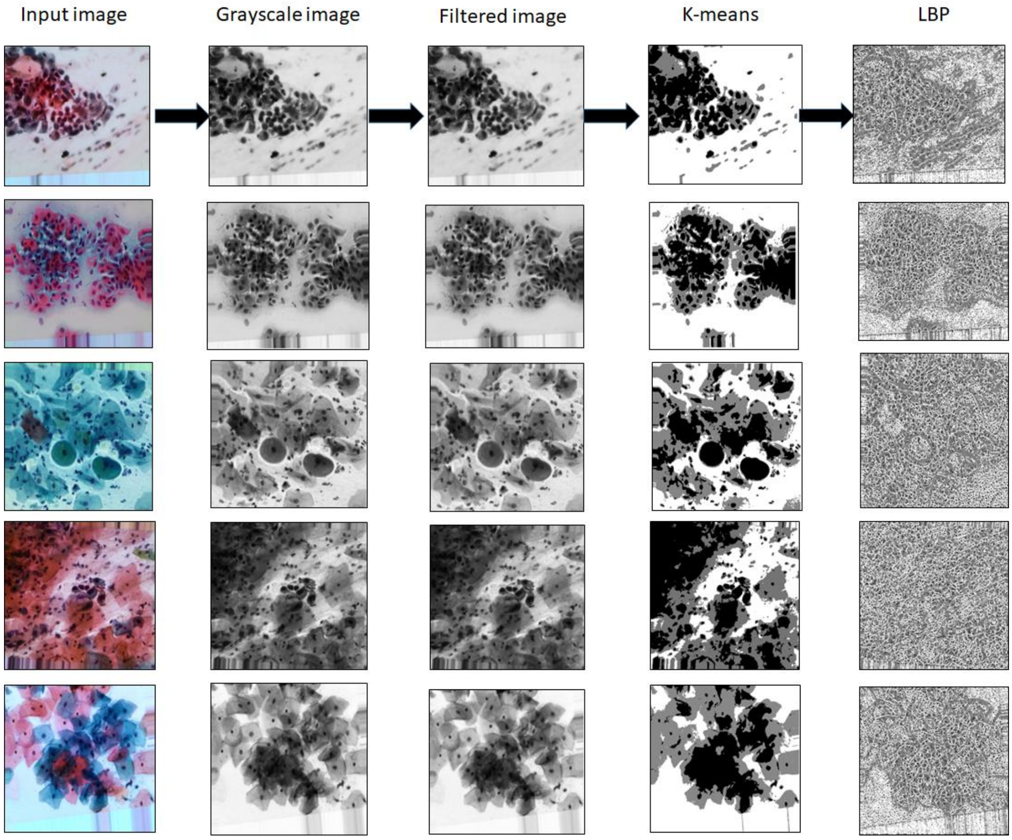

Figure 7: *Classification of cervical cancer images.*

Figure7 denotes the classification of cervical cancer image samples illustrating classification process of input images, grayscale images, filtered images, k means segmentation and LBP feature extraction providing a clear images to understanding the diagnosis cervical cancer.

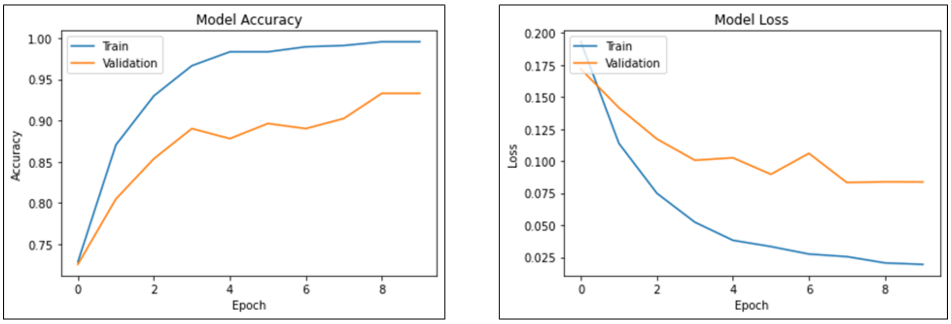

Figure 8: *Models of Accuracy and Loss.*

Figure 8 represents models of accuracy and loss that demonstrate train and validation of deep learning classification applied to the cervical cancer diagnosis. These models illustrate the effectiveness of the training process, showcasing the system learns to distinguish between different classifiers while minimizing error across both training and validation datasets.

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Table 1: *Comparison classification of accuracy in cervical cancer detection*

METHOD	ACCURACY
CSOANN	96%
SVM [11]	91.5%
KNN [12]	88.17%

Table 1 represents a comparison of various classification methods for cervical cancer detection, highlighting that the CSOANN model achieves the highest accuracy at 96%, significantly outperforming the SVM model at 91.5% and the KNN model at 88.17%.

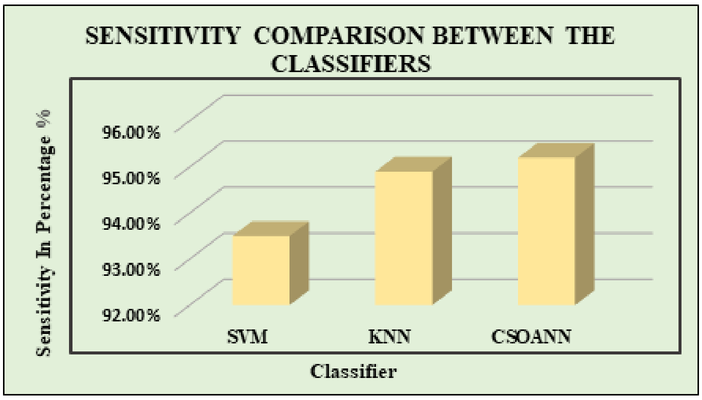

Figure 9: *Sensitivity graph of cervical cancer classifier.*

Figure 9 denotes the analysis of sensitivity in cervical cancer by presenting a detailed comparison of diagnosis performance across different classification techniques. The results of graph indicate that the CSOANN classifier demonstrates a superior sensitivity at 95.2%, outperforming both the classifiers SVM [11] at 93.5% and KNN [15] at 94.9%.

4 Conclusion

Cervical cancer is a widespread gynecological disease worldwide, representing a major threat to women's health. Therefore, this research presents a cervical cancer detection through advanced image processing techniques. By implementing AMF successfully reduced noise in cervical images while maintaining critical details necessary for accurate diagnosis. The segmentation of these images using the K-means clustering algorithm effectively isolated ROI, allowing for precise identification of cervical cancer. The integration of LBP for feature extraction by capturing essential texture information, which is used for extracting informative features from single cell images in cervical cancer detection. The application of the CSOANN classification remarkable of accuracy and sensitivity that outperforming traditional methods. The proposed workflow significantly enhances diagnostic accuracy and sensitivity, which are crucial for improving patient outcomes in cervical cancer management. The high classification

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accuracy of 96% and sensitivity 95.2% achieved by the CSOANN indicate its potential as a reliable for cervical cancer.

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