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# Hybrid Decision Fusion based Multimodal Ensemble Framework for Cervical Cancer Detection

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**ABSTRACT**

Cervical cancer is fourth in the list of cancers that affect women. It has remained the main cause of death for women in developing nations. The cancer is spread through human papilloma virus (HPV), which is sexually transmitted. Pap smear and colposcopy image analysis remain prominent methods of diagnosis. These screening tests require skilled diagnostic experts, a scarce resource in developing countries thus restricting the effectiveness of the cancer detection process in large scale. Machine learning and deep learning are branches of artificial intelligence that are being used increasingly in cancer diagnosis. This study proposes a novel hybrid intelligent system for cervical cancer detection. A hybrid model of feature extraction and feature fusion is proposed for merging the two-state image and clinical data. Subsequently a machine learning ensemble learner is assembled to classify the features. The model performed with a satisfactory accuracy of 96.16%. Our results show that our method outperforms state of the art approaches and archives better, dependable accuracy.

**Keywords:** Cervical Cancer, Deep Learning, Machine Learning, Ensemble Methods, Support Vector Machine

## I. INTRODUCTION

Cancer is genetically triggered condition that more often than not results in death. Cervical cancer is one of the prominent reasons for cancer related death in women, mainly in developing countries [1]. It can be diagnosed through pap smear, colposcope, and biopsy screening tests. These tests require expensive medical imaging devices and experienced diagnostic experts. These resources are limited underdeveloped/developing nations where the highest number of deaths due to cervical cancer are recorded [2]. Human papilloma virus (HPV), a sexually transmitted infection is identified as the source of the cancer[3]. Nevertheless, all HPV infections do not turn malignant indicating there are some synergistic factors that are acting as accelerators in turning the cells malignant [4]. Lifestyle and medical factors like history of sexually transmitted illness, hormonal contraceptives, smoking, number of pregnancies, increased number of sexual partners, are found to be few critical driving factors that turn the cervix cancerous [5][6]. Intelligent systems for diagnosing cervical cancer deal with image processing (pap smear, colposcope, magnetic resonance image) [7] [8]. Although there are few studies aimed to fusing the clinical & pathological reports with the images, they suffer from methodological fallibility. To overcome these drawbacks, this paper aims to build a hybrid classification model that extracts features from cervix images and fuses them with selected features of corresponding clinical reports via decision level fusion technique. A combination of machine learning (ML) and deep learning (DL) models are assembled and trained to predict the presence of cervical cancer. To the best of our knowledge, the exact line of methodology hasn't been experimented so far.

The paper is structured in the following way. Section II refers to related work, section III presents the proposed methodology, section IV presents the implementation and evaluation of results in the current experiment. Section V concludes the paper.

## II. RELATED LITERATURE

Exploring the risk factor in addition to clinical attributes has been the point of interest to several recent studies. Deng et al. [6] discussed the use of machine learning algorithms to analyse the risk attributes and find patterns resulting in cancer. He has deployed popular models of SVM (Support Vector Machine), XGBoost (eXtreme Gradient Boosting) and Random Forest. Since random forest has an inbuilt feature selection method, authors use that as the primary feature selector followed by the above models and reported accuracies of 91.98, 95.59, and 97.06 respectively. Ahishakiye et al. [9] extended the ML algorithms using an ensemble algorithm to combine the individual model's best predictions and have achieved an accuracy of 87.21%. Several works utilized ensemble learners of major ML algorithms like KNN, Naïve Bayes, random forest, adaboost etc[6]. Koruru et al. [10] conducted elaborate study on ML techniques that have been applied widely in the literature for the case study of cancer prediction and prognosis and affirmed that ML has the potential to accurately predict the cancer prognosis. Moldovan [11] modified the SVM with a chicken swarm optimization technique to achieve 94.3% accuracy[11]. Parallelly, Fernandes et al. [12] employed autoencoders to predict the biopsy outcome of cervical cancer candidates and claimed a superior performance. Ijas et al. [13] designed CCPM (cervical cancer prediction model) using Density-Based Spatial Noise Cluster (DBSCAN) and isolation forest (iForest) and reported satisfactory result 97.22%. So far, the credibility of these models was tested on a single dataset containing risk factors of cervical cancer.

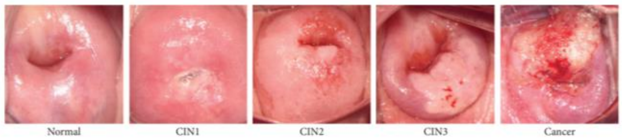


Fig 1: colposcope images displaying the progression of cervical cancer

Intelligent systems for image processing in medical diagnosis is popularly handled by deep learning division of artificial intelligence [14]. Pap smear images [15], colposcope images[16], magnetic resonance image MRI [17] and computerized tomography CT [18] images are examined for cervical cancer detection. Current study focuses on colposcope images that are segmented and classified using methods like convolution neural networks [19], extreme learning machines [20]. The pap smear, CT and MRI image analysis is beyond the scope of this paper. As for the cervix images, segmentation is done in two levels. Firstly, the cervix region is extracted using ML models like gaussian mixture modelling [21], k means clustering [22], artificial neural networks [23], convolution neural networks. Secondly, the image is examined for extraction of acetowhite lesions (AW) that are critical indicators of malignancies [19]. AW segmentation and classification is done by faster RCNN [24], Mask RCNN[25], deeplab V3[26], squeezenet. These methods have a drawback of having to diagnose from a single cervix image alone.

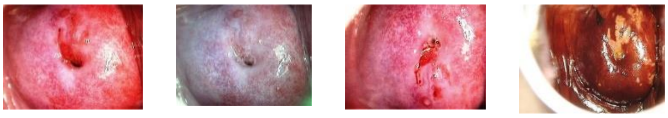

Fig 2: Different cervix images demonstrating the malignant areas.

A simple summary of the above methods is that they are individually prone to errors and misdiagnosis. Fusing features from clinical data and image data is a way forward to develop a dependable model that can work on multimodal information.

Li et al. (2020) built a graph convolutional network with edge features (E-GCN) noted a 78.33% accuracy from using time series image features [27]. Perkin et al. (2022) [28] contradicted these findings by fusing 17 time series images of colposcope images. The study reported no meaningful increase in accuracy after the analysis of 17 images. It provides a scope to ponder over other the possibility of adding non image information to meaningfully increase the classification accuracy. Peng et al. (2021) has analysed multimodal feature changes by building a multistate convolution neural network over genetic algorithm. They declared 86.3% accuracy[29]. On the other hand, Yinuo Fan et al. (2022) [24] built a colposcopic multimodal fusion convolutional neural network (CMF-CNN) that made use of Squeeze-and-Excitation fusion to combine to achieve 92.70% accuracy. The current study proposes a modal level feature extraction using EfficientNet encoding and random forest algorithms. The extracted features are fused at decision level and subsequently classified through ML algorithms. Finally, a soft voting ensemble learner is assembled to complete the mode.

## III. METHODS AND MATERIAL

The schematic architecture of the proposed model is given in Fig 3. The work flow contains 8 modules: cervix image cropping with GMM, specular reflection removal from the cropped image, feature extraction using EfficientNet, clinical feature selection using random forest, decision level fusion of the features, classification using KNN, SVM, RF, soft voting ensemble to aggregate the results.

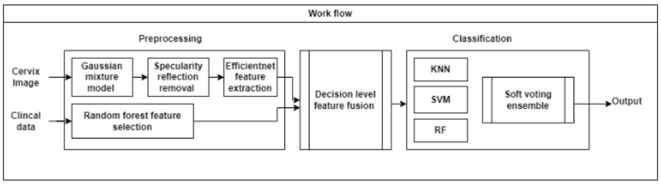


Fig 3: Block diagram of proposed methodology

### A. Gaussian mixture model for cervix ROI extraction

The cervix image more often than not consists of surrounding noise and unwanted material like speculum, vaginal walls etc. GMMs are a type of unsupervised clustering algorithm which can be used to partition data into distinct groups or clusters. By using a GMM, the image can be segmented into different regions based on their similarity in terms of color, texture, and shape. GMMs can also be used to identify and segment objects from the background, making them useful for object detection.

To efficiently classify, the cervix region must be cropped with precision. Srinivasan et al. [30] modified GMM in terms of expectation maximization to achieve a seamless segmentation. For x € ℝd , a gaussian model can be expressed as considering K items' as gaussian density components where the parameters μk and ∑k each being a multivariate gaussian density.

$$pk\ (x|\theta k) = \frac{1}{(2\pi)^{d/2} |\sum k|^{1/2}} e^{-1/2 (x-\mu k) \sum (x-\mu k)}$$

Where $\theta k = \{\mu k, \sum k\}$. GMM is considered one of the few top choices for segmenting medical images. Hence, we adopted the same for ROI extraction.

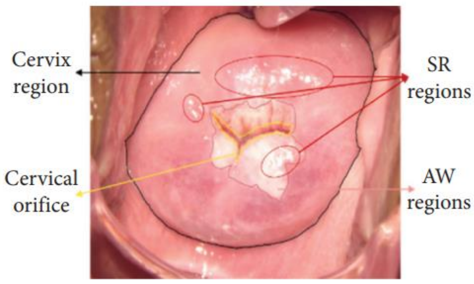


Fig 4: Region of Interest marked around the cervix

### B. Specular reflection removal

The moisture on the cervix region reflects the focus light. As a result, white colour refractions with high saturation pixels are observed. These regions must be pre processed before classification because they morphologically mimic the acetowhite lesions, which are the key features indicating cancer. By converting the RGB (red, green, blue) image to HSI (hue, saturation, intensity) format, we have added a threshold for the intensity component and extracted SR pixels. These pixels are removed and replaced mean of the surrounding pixel colour.

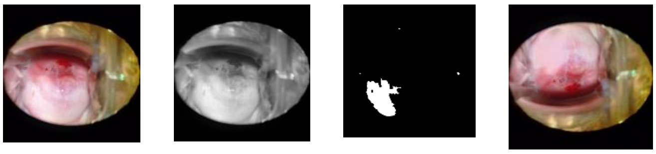

Fig 5: Specular reflection removal stages

### C. Transfer learning mixture model for cervix ROI extraction

Typically, convolutional neural network training requires a significant amount of data and computational resources. Although, occasionally, it is challenging to assemble a sizable amount of data for classification purposes. However, it can be exceedingly challenging to match training and testing data in the context of real-world problems. Transfer learning is a solution to the above problem. Transfer learning is one of the most sophisticated machine learning techniques that can learn the information needed to solve a classification task and then reuse that training to solve domain relevant tasks. Transfer learning principles are used to extract features from cervix images, which are then categorized using various machine learning classifiers to increase accuracy.

### D. Feature extraction

Using the CNN encoder network, features are extracted from the input images and various types of attributes are generated. The EfficientNet B3 architecture was used to extract image modality features from the cervix images. It is observed that the white colour abnormalities and clumps are the key features. EfficientNet architecture is an ImageNet model trained on a million images [31]. In general, the EfficientNet models outperform previous CNNs in terms of efficiency and accuracy [32]. The iconic property of EfficientNet is that it applies uniform scaling on depth/width/resolution through compound co-efficient. The conventional EfficientNet is enhanced to better learn the features. The convolution function used by EfficientNet is given as:

$$a(m,n) * b(m,n) = \sum_{z=-\propto}^{\propto} \sum_{z_2=-\propto}^{\propto} a(z_1,z_2) \cdot b(m-z_1, n-z_2)$$

Random forest feature selection strategy is widely used when the data has multiple closely correlated attributes. We have employed the RF feature selection strategy for the clinical data. It basically ensures there is variance ‘v’ to a certain threshold level. Due to the observed variance, the model thus prunes strongly correlated attributes leaving selected features. Variance is given by:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i-\mu)^2$$

The features shortlisted by deep learning’s EfficientNet and machine learning’s random forest are then fused together to form meaningful values in vector subspace.

### E. Feature fusion

According to Perkins et al. [28], fusing time-lapsed images of the cervix does not meaningfully improve classification accuracy over a single image. So, once the features are extracted, the features from clinical data and features of the corresponding image are fused. There are two types of feature fusion methods feature level fusion (i.e., vector concatenation) and decision level fusion (i.e., majority voting). Decision level fusion works by merging the predictions from unimodal results through majority voting. By combining image and clinical data, we may extract characteristics from a variety of sources and utilize them to create a model that is more accurate and stable. Studies have shown that the use of multimodal learning is more robust and dependable than unimodal work.

### F. Classification

The above fused features are fed into three state of art machine learning algorithms support vector machine (SVM), K nearest neighbours (KNN), and random forest (RF). Classification in machine learning is the process of predicting the class or category of an input data instance, in this case, the binary classification of cancer.

1) SVM:

Support vector machine works by classifying the data points by creating a hyper-margin between the elements of data. The objective function of SVM is to maximize the margin distance. The hyperplanes are divided by the distance and direction vectors. Hyper plane eq is given as:

$$w = \sum_{i=1}^{n} \alpha_i \, y_i x_i$$

1) KNN:

K nearest neighbour is a non-parametric algorithm that does not have any prior information in the data. The algorithm groups the data into clusters using a distance measure. The objective function of the algorithm is to minimize the distance within a class. Traditionally KNN uses Euclidian distance measure, but in the current study we are using a city block measure considering the image nature of the data. The city block distance equation is given as:

$$C(d) = \|p - q\|_1 = \sum_{i=1}^{n} p_i - q_i$$

2) RF:

Random forest is an ensemble of decision trees clubbed with boosting and bagging techniques to escape overfitting. N-estimators (number of decision trees), criterion (a measure ensuring the quality of the split) are key hyperparameters. Criterion is internally supported by gini index and entropy functions.

Through probability p, gini index is calculated by x

$$H = 1 - \sum_{i=1}^{n} (p_i)^2$$

### G. Ensemble learner

Ensemble learning is a strategy where the base learner prediction scores are taken and ensemble output is generated. Once the base classifiers are trained on the data, in order to get a final prediction result that is more accurate than that of individual base classifiers, the prediction outcomes of all classifiers are combined using a soft voting ensemble approach. It is a synthesis of the mean and weighted majority voting methods. As for assigning the weights, we plainly examine the performance of all basic classifiers and we then allocate larger weights to the classifiers that deliver better results. Theorizing that we have N number of weights w1, w2,.. wn, that are taken on the basis of output of

$$\mu(x) = \frac{1}{N} \sum_{n=1}^{N} \omega_n d_{n,c}(x)$$

post which there are N*C classes and specifically allotted weights. The support for each class is obtained by:

$$\mu(x) = \frac{1}{N} \sum_{n=1}^{N} \omega_{n,c} d_{n,c}(x)$$

## IV. RESULTS AND DISCUSSION

The image processing module was developed in Python language which uses TensorFlow and Keras libraries for the development of the said model. The model was implemented on Intel Xeon W-2233-based workstation, 32 GB RAM, 1 TB HDD, and 256 SSD processor. The GPU is NVIDIA Quadrop P5000 32 GB. Libraries like OpenCV, matplotlib, etc., were used. Experimental dataset is obtained from a private source with ethical use waived. We have trained the model in 5 folds of cross validation and 50 epochs. The training accuracy gradually progressed with respect to the epoch's number and reached the maximum in 43rd epoch. The training accuracy of 97.1% was noted for the hybrid model proposed in this study. To the best of our knowledge and extensive literature survey, ours is the highest accuracy in relevance to similar hybrid models who used image and clinical data as inputs. The performance plot for the proposed model is given in figure III.

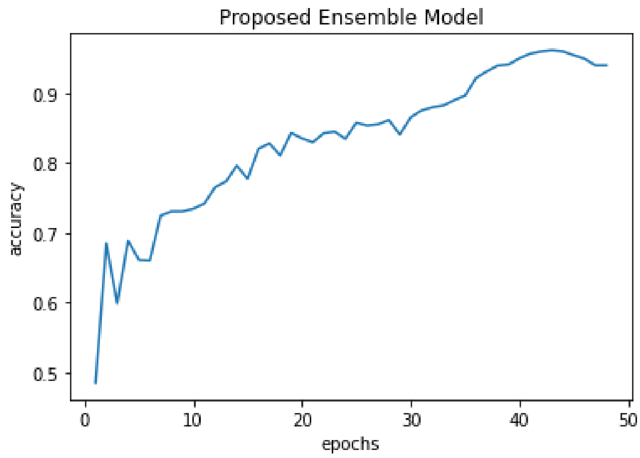


Fig 5: Accuracy plot of the proposed model

We have used accuracy as a basic performance metric and precision, recall, f-1 scores as supporting metrics. True Negative (TN) and True positive (TP) are the instances where the model predicts the negative and positive cases accurately. False Positives (FP) are the mistaken positive forecast, whereas False Negative (FN) is the incorrect negative prediction. When these measures are applied to a multiclass issue with N classes, a confusion matrix is generated, with columns representing the real class and rows representing the anticipated class. Equations below are the mathematical formulations for the evaluation metrics obtained from the confusion matrix.

$$Accuracy = \frac{TP1 + TN1}{TP1 + FP1 + TN1 + FN1}$$

$$Recall = \frac{TP1}{TP1 + FN1}$$

$$Precision = \frac{TP1}{TP1 + FP1}$$

$$F1 - Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$$

The model performed with accuracy of 92.86 % ,91.32 %, 94.18 % for SVM, KNN and RF. The ensemble combined the base classifiers prediction scores and attained 96.16% of accuracy. Table 1 displays the results in a comparative fashion.

Table I: Performance comparison

| Study | Accuracy (%) |
|---|---|
| [27] Li et al. (2020) | 78.33% |
| [28] Peng et al. (2021) | 86.3% |
| [25] Yinuo Fan et al. (2022) | 92.70% |
| Proposed | **96.16%** |

## V. CONCLUSION

In this paper, a hybrid technique based on amalgamation of deep and machine learning algorithms is proposed using the concept of transfer learning. The developed framework can be utilized for support in medical diagnosis. Features are extracted through EfficientNet model and random forest method. They are further classified by state-of-the-art machine learning models of SVM, KNN, and RF. Subsequently, a soft voting ensemble learner is trained to arrive at the final result. The ensemble model performed with an accuracy of 96.16%. To the best of our knowledge, the proposed hybrid model is novel and has not been used so far. The model displayed a satisfactory accuracy and this can be used as a base for multimodal classification for cervical cancer identification.

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