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IDENTIFICATION AND CLASSIFICATION OF CERVICAL CANCER USING CONVOLUTIONAL NEURAL NETWORK BASED ON FISHER SCORE

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Abstract— Cervical cancer is one of the top reasons why women die from cancer. With early discovery and treatment, the challenges associated with this cancer may be minimized. The main goal of this research paper is to identify and classify cervical cancer using the Fisher Score-Convolutional Neural Network (FS-CNN). The data is collected from open-source database and then the unwanted noise in images were removed using central filter. This research is carried out to prevent problems occurring due to late diagnosis by ensuring early diagnosis and classification of cervical cancer. In order to classify the normal and abnormal cells as well as the types of abnormal cells, we enhance the weight of the Fisher Score-Convolutional Neural Network (FS-CNN) algorithm. With the aid of Fisher score, the proposed classification approach is chosen in order to enhance the use of CNN design parameters. The research confirms that deep learning techniques are helpful in early detection and classification of cervical cancer images. Accuracy metrics are employed to check performance and image quality assessments.
Keywords: Classification, feature selection, prediction, the Fisher Score - Convolutional Neural Network (FS-CNN), Cervical cancer

INTRODUCTION

The health of women is in danger from the malignant tumor condition known as cervical cancer. According to research and studies, tens of thousands of new instances of cervical cancer are reported each year globally, seriously jeopardizing the health and safety of women. Around 85% of cervical cancer patients come from poor nations. Early detection and treatment can prevent the condition from getting worse and reduce the likelihood of death.

Effective evidence for the early detection and treatment of cervical cancer in industrialized nations comes from clinical application. The majority of cervical cancer patients are already at an advanced stage of the illness when they are detected in countries and regions with relatively lagging economic and medical circumstances which results in a lesser cure rate and a higher mortality rate. Consequently, looking for practical and effective cervical cancer screening methods can offer crucial supplementary judgement indications for defining and diagnosing the condition and establish a solid scientific basis for choosing therapeutic treatment alternatives.

Medical images are also too complicated and varied to obtain a flawless annotation which always results in noisy label. To solve these challenges and successfully locate cervical cells in multi-cell images with cell overlapping and clusters, we propose employing CNN-based object recognition to proactively extract and learn task-specific properties.

Developing countries such as India have challenges in managing a rising number of patients on a daily basis. The relevance of machine learning may be demonstrated in a wide range of sectors since it delivers varied benefits in task completion. Medical image analysis is performed in the medical form for diagnostic purposes by producing images of the structures and activities within the body. The application of machine learning for medical image analysis gives several benefits during disease diagnosis. Convolutional Neural Network-Conditional Random Fields offers a variety of applications for assessing and recording images of the human body's internal structure. Machine learning technologies such as neural networks and CT scans aid in the analysis of many sorts of medical images. Machine learning has had the greatest impact on medical image analysis.

These algorithms may aid in the exact and objective diagnosis of cervical cancer in hospitals in countries with high mortality and poor screening rates. To investigate the efficacy of the scoring system for cervical cancer screening and early detection using big data analysis. Data from the investigations were statistically examined and processed.

As one of the supervised feature selection methods, the Fisher score algorithm selects each feature independently in accordance with their scores. Feature selection strategies can escape the curse of dimensionality and so enable model reduction, making it easier for researchers to evaluate experimental data.

The survey of the proposed study is shortly described in Category 2 and Category 3 presents the proposed study for identifying and to classify cervical cancer. The implementation results are discussed in Category 4, and the study's conclusion is presented in Category 5.

LITERATURE SURVEY

Deep learning was created to extract significant data from databases and to choose select attributes in order to overcome the traditional difficulty with neural restoration procedures.

Neha Sharma *et al.* [1] investigated CNN for image classification and the proposed CNN algorithm is compared with Alex Nets,GoogLeNets and ResNet50. Objects are recognized with better precision using GoogLeNet and ResNet50 when compared to AlexNet.

Ahmed Ghoneim *et al.* [2] proposed cervical cancer cell detection and classification system based on convolutional neural networks (CNNs). Deep-learning features are extracted from CNN model after feeding input images and it also Extreme Learning Machine (ELM) is used to perform classification of the cervical type. Transfer learning is used to apply the CNNs paradigm. Moreover, the suggested technique is compared to multi-layer perceptron (MLP) and autoencoder (AE) algorithms, demonstrating that the CNN-ELM-based system obtained 99.5% accuracy when compared to other algorithms.

Chengzhang Li *et al.* [3] suggested that the Fisher score technique was used in conjunction with the Maximal Clique Centrality (MCC) approach to discover hub genes. If P 0.05 in their survival study, it indicates that Fisher score-selected hub genes were related with lower survival time. The Fisher score method is contrasted with the Weighted gene coexpression network analysis (WGCNA), Lasso, and random forest algorithms. As compared to other algorithms, the Fisher score followed by utilizing the MCC method is better.

Mingyuan Xin *et al.* [4] proposed an Innovative depth neural network training criteria for maximal interval minimal classification error. M3 CE-CEc performed well in both datasets, MNIST and CIFAR-10 making sure deep CNN has better performance.

Zhong Qu *et al.* [5] suggested that the algorithm scales the network model horizontally and accesses the convolution layer with the kernel size of 1 X 1, 3X 3 by utilising VGG16 to increase the efficiency of crack detection. The suggested method classifies cracks first and then uses CNN to identify the classified crack images.

Muhammed Niyas *et al.* [6] proposed that SVM and KNN algorithms provide less accuracy as compared to Fisher score and Greedy search method that achieved 90% performance accuracy for feature selection.

Lin Sun *et al*. [14] proposed a unique feature selection strategy in multilabel neighborhood decision systems based on Fisher score and multilabel neighborhood rough sets (MNRS). To fit multilabel data, a mutual information-based Fisher score model with a second-order correlation between labels is used. To improve classification performance on multilabel datasets, a filter-wrapper preprocessing technique for feature selection based on the modified Fisher score model is suggested.

Venkatesan Chandran *et al.* [15] proposed that in the realm of deep learning, the convolutional neural network (CNN) model outperforms others in the classification of cervical cancer type. The VGG19 (TL) model and CYENET are two proposed deep learning techniques for detecting cervical cancer using colposcopy images. VGG19 has a classification accuracy of 73.3%. The

CYENET model has a classification accuracy of 92.3%, which is 19% higher than the VGG19 (TL) model.

Mavra Mehmood *et al.* [16] presents CervDetect, a method that use machine learning algorithms to assess the risk factors for malignant cervical development. CervDetect selects efficient features using the Random Forest (RF) feature selection approach. CervDetect detects Cervical Cancer with 93.6% accuracy by integrating RF and shallow neural networks.

Mohamed Ibrahim Waly *et al*. [29] develops an intelligent deep convolutional neural network for cervical cancer detection and classification (IDCNN-CDC) model utilising biological pap smear images. Originally, the Gaussian filter (GF) approach is used to improve data in the Pap smear image by removing noise. The TE-DFO algorithm calculates picture segmentation in order to correctly detect sick regions. The weighted extreme learning machine (ELM) classification model is used to identify and classify cervix cells where its sensitivity, specificity, accuracy, and F-Score are examined.

PROPOSED TECHNIQUE

Our planned study's major objective is to identify and categorize cervical cancer. Deep learning techniques were utilized to train a convolutional neural network to recognize three different types of cervical cells as well as healthy (non-cancerous) cells from an image dataset in the study. Deep learning techniques were utilized to train a convolutional neural network to recognize three different types of cervical cells as well as healthy (non-cancerous) cells from an image dataset in the study. In order to improve the quality of the input data, a set of input data is required for data preparation. During data preparation, lost values, labelling errors, noise, imbalances and excessive dimensionality are also eliminated. The Gabor filter with histogram equalization has been employed to extract texture information from these images, while the Unsharp filter was utilized to extract edge features. The pre-processed image's Region Of Interest (ROI) is now processed finishing concluding the Data Pre-processing stage. Thus, part of an image which is relevant for classification gets spotted whereas histogram enhances the contrast of an image. The proposed model is executed in python with various cervical cancer detection techniques and metrics. Figure 1 shows the workflow of the proposed technique.

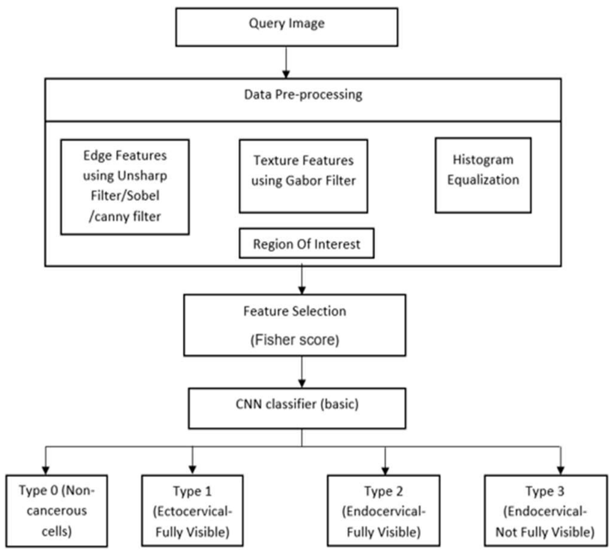

Figure 1: *Block diagram of the Proposed technique*

The arrangement model for cervical malignancy events works in four steps.

Step 1: Constant information gathering for cervical cancer disease

Step 2: Data-preprocessing technique

Step 3: Feature selection by fisher score

Step 4: Classification utilizing CNN

3.1 Preprocessing:

This approach is initially implemented into the suggested model in order to obtain a better version of images that enhances specific image attributes for subsequent processing. This technique simplifies interpretation and application, resulting in more accurate prediction. This proposed investigation employs the preprocessing work of image resizing, followed by obtaining edge features using the Unsharp filter, obtaining texture features using Gabor filter with histogram equalization and finding the Region of Interest (ROI). This improves the precision with which a variety of conventional classifiers are organized.

Image resize:

Image Resizing is a technique that allows to make image smaller or larger without cutting anything out. Various image size in dataset is made into smaller base size since machine learning models train faster on smaller images. In this research, dataset having different sizes of Images are resized to a base size using the resize () method on the new image instance, supplying a tuple argument with two integers to determine the width and height that are desired so as to train models faster.

Unsharp filter:

The unsharp filter is a straightforward sharpening operator that improves edges as well as other high frequency components in an image by subtracting an unsharp or smoothed version of the original image.

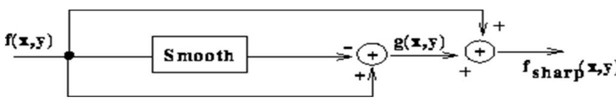

Figure 2: *The complete unsharp filtering operator*

For the reasonable dataset, the accompanying formula of unsharp sharpening operator is utilized:

$$fsharp(x, y) = f(x, y) + c * g(x, y) \qquad (1)$$

where c is a scaling constant and c values ranges from 0.2 to 0.7, with higher values enabling increasing levels of sharpness.

Gabor filter:

Gabor filters are bandpass filters in image processing that are used to extract features and analyse texture. The impulse response of these filters is generated by multiplying a Gaussian envelope function by a complex oscillation. The transfer function G(k) of a Gabor filter (Fourier transform of the impulse response) is given by:

$$G_{mn}(k) = e^{-\frac{1}{2}(k - k_{0mn})^T (A_{mn}^{-1})^T (k - k_{0mn})} \qquad (2)$$

where k = [k1 k2] ^{T} is the spatial frequency.

The suggested framework evaluates pre-mission, bring out selection using ROI over unbalanced informative indices for the pre-processing technique. The medically modified dataset is used to evaluate the observations [24].

3.2 Feature selection:

In this phase, The Fisher score is used in the selection of features. The Fisher score is a popular supervised feature selection approach. Its primary goal is to locate a feature subset in a data space spanned by the selected features. It seeks a subset of attributes that maximize the lower bound of the typical Fisher score. It can consider feature combinations and eliminating superfluous features.

Steps to be followed while utilizing Fisher score algorithm for feature selection:

- ❖ Construct the affinity matrix W in fisher score way.
- ❖ Build the diagonal D matrix from an affinity matrix W.
- ❖ Compute the numerator and denominator for Lr avoiding denominator of Lr to be 0.
- ❖ Compute fisher score from Laplacian score, where fisher score = 1/lap_score – 1.
- ❖ For the r-th feature, we define fr = X(:,r), D = diag(W*ones), ones = [1,...,1]', L = D - W
- ❖ Let fr_hat = fr - (fr'*D*ones) *ones/(ones'*D*ones)
- ❖ Fisher score for the r-th feature is score = (fr_hat'*D*fr_hat)/(fr_hat'*L*fr_hat)-1

In this proposed feature selection using Fisher score algorithm, the original feature count of 31 is reduced to 27 optimal features.

3.3. Classification Using Convolutional Neural Network (CNN) based on Fisher score

Clinical images are categorized using the convolutional neural classifier [28]. The layout of CNN's Fisher score model is shown in Figure 2.1. Average pooling concept has been used to determine the number of pooling layers. The first convolutional layer has 64 channels of size 5 × 5 in while the second convolutional layer has 128 channels of size 5 × 5. The pitch of the channels is 2 pixels. The maximum size of the pool channel cover is 2 × 2. After the next level of maximum grouping, the weights are levelled and managed on an entirely related level. A SoftMax (performance) level occurs after two levels that are totally connected. Adam compiler is used to train Adam is an optimization technique may be used to iteratively update network weights based on training data.

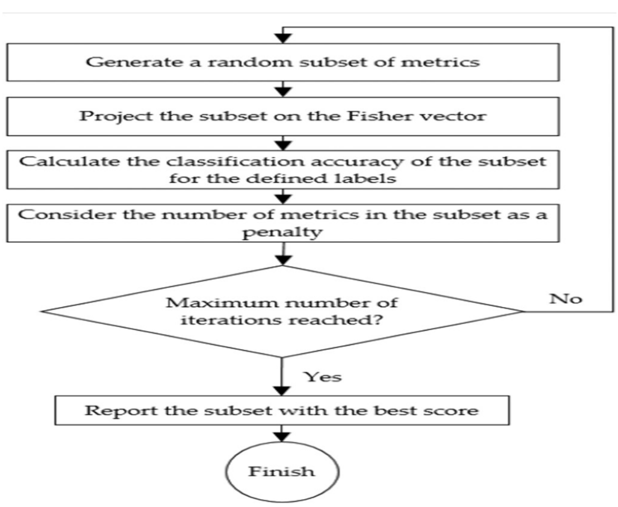

***Figure 2.1**: Flow diagram of proposed algorithm*

The rectified linear activation function is a straightforward calculation that simply returns the value offered as input. The neural network employs ReLU activation to aid in the comprehension of complex data patterns. As illustrated in Fig. 2.2, each of the hidden layers makes advantage of the ReLU implementation work. It is depicted as,

$$F(\Omega) = Max(0, \Omega)$$

(3)

Where Ω is the contribution of the neurons. The limitless initiation work has been removed from the ReLU enhancement work. The connecting layer connects the various characteristics supplied by the other component. Overfitting issue in the model is reduced by using the neighborhood response standardization following each connection layer after the channel standardization of the initiation capacity is completed. It is found in equation (3).

$$\Omega_x = \frac{\Omega_x}{\left(A + \left(\gamma \sum_y \Omega_y^2\right)\right)^{\alpha}}$$

(4)

In equation (4), the terms A , γ and $\alpha \in R$ are hyperparameters and Ω_x are the input pixel esteem respectively.

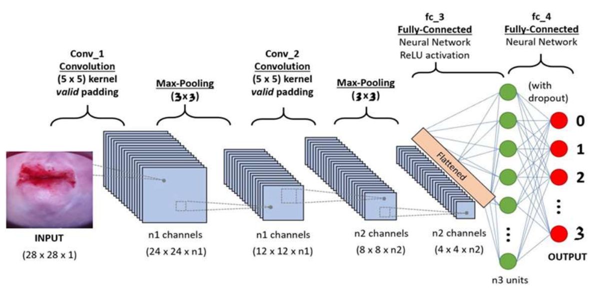

Figure 2.2: *Pictorial representation of CNN layers*

3.4. Dataset Description

The dataset has 6791 images containing 6734 colposcopy images derived from Kaggle - Intel and Mobile Optical Detection Technologies Cervical Screening Dataset and 100 normal images were also picked randomly from internet sources. The declaration is distinguished by considering on the area of apparent change in the context of the suggestive review. The cervix is frequently found in two regions: the Squamo-columnar junction (SCJ)-2, which connects various types of epithelial cells, and the transformation zone, which is the region between the primary SCJ and the completely new SCJ. The dataset comprises three types of cervical cancer cells discovered in the transformation zone. It includes various transformation zone spots corresponding to various cervical types.

Also, few normal (non-cancerous) cell images are included in dataset to differentiate between the two. Now the dataset used for the model consists of three types of cervical malignant cells as well as normal (non-cancerous cells). Cervical type 2 and cervical type 3 may have hidden lesions that necessitate different treatment. The total number of images in the dataset is 6791, with 1191 samples of type 1, 3567 samples of type 2, 1976 samples of type 3 and 100 samples of normal (non-cancerous) cells. A total of 1300 images were collected for processing as samples containing 400 of each cancerous cell type and 100 of which were normal (non-cancerous) cells. Images in the dataset have different sizes like 640*800,363*360,302*366,3096*4128 etc., which are then resized to a base size of 300*300 to train models faster.

The dataset is preprocessed in order to identify the Region of Interest (ROI) in a way to get the relevant portion of the image, which is accomplished by employing coordinate points that are only focused on cervical cancer cells. Moreover, information enhancement tactics are employed to keep the scope of information preparation up to date. The strategy of information improvement is utilized to increase the model's reliability. The unsharp filter is a basic sharpening filter that improves the edges of the image. Gabor filtering is a linear texture analysis filter. When the input picture is convolved with all the Gabor filters, the patterns are easily emphasized, and the response is maximum near edges and points where texture changes. The histogram equalization method is used to process images in order to improve an image's contrast by adjusting the intensity distribution of the histogram. The goal of this strategy is to give the cumulative probability function a linear trend associated with the image. All modified visual information is scaled over time for CNN to suit the model.

Sample Images:

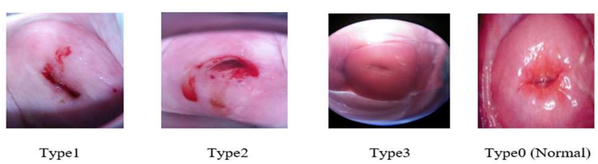

Figure 3: *Sample images in dataset*

IV EXPERIMENTAL RESULTS

The outcomes are the consequence of a component-specific method for handling computer components: 8 GB of Memory, Intel core CPU, 64-bit operating system and Microsoft Windows 11. Python is used as the foundation for a distinct categorization of cervical cancer in convolutional neural networks based on the Fisher score approach to anticipate the types of abnormal cell detection.

4.1. Quality Metrics

To calculate the effectiveness of the predicted model, an evaluation measure is used. It contains numerous measurements that use the standard key estimation approach. We use and choose measures such as accuracy, precision, recall, and F-measure for our estimate idea. If we consider accuracy to be a single metric, we can attain 93% accuracy and identify nearly all the data from medical testing when True Positive (T_p), False Positive (F_p), True Negative (T_n) and False Negative (F_n) are considered.

Accuracy: The predicted technique's accuracy is the ratio of the total amount of True Positive (T_p) and True Negative (T_n) to the total quantity of data.

$$\text{Accuracy (A)}=\frac{T_P+T}{T_P+T_n+F_p+F_n} \tag{5}$$

Precision: The precision of this study measures the proportion of individuals who are anticipated to be at risk of developing when cervical image segmentation and classification are performed.

$$Precision\ (P) = \frac{T_P}{Tp+F_p} \tag{6}$$

Recall/Sensitivity: This research examines the proportion of those who were at risk of developing cervical cancer and who were at risk of developing cervical cancer according to the algorithm.

$$\text{Recall(R)} = \frac{T_P}{(T_P+F_n)} \tag{7}$$

$$\text{F-measure}=\frac{(\alpha^2+1)P\times R}{\alpha^2(P+R)} \tag{8}$$

Where Precision and Recall are represented as P and R; F1 score can be received when α set to 1. Upgrade suggestions should now be more specific.

Using a GUI, the categorization could be observed for training and testing in real time. The training results will be displayed in terms of performance metrics after feeding the training dataset into the GUI as follows.:

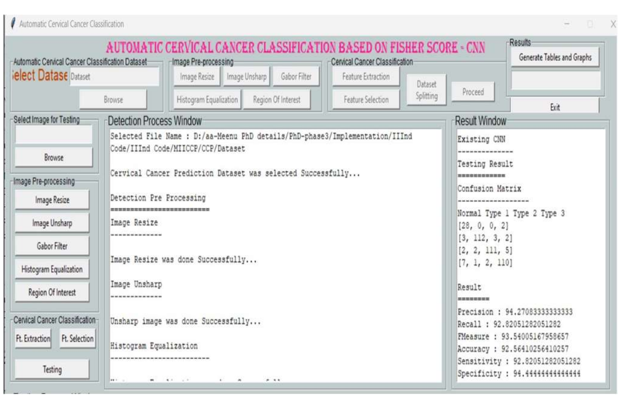

Figure 4: *Training metrics of fisher score-CNN model*

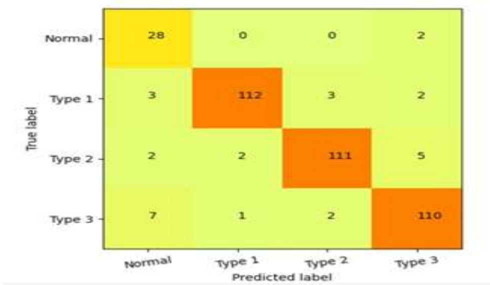

Figure 5: *Confusion Matrix of the proposed fisher score-CNN model*

Figure 4 shows a snapshot of the proposed fisher score - CNN GUI with training phase sample. The suggested fisher score-CNN model had a validation accuracy of 92.56%. Figure 5 indicates the proposed Fisher score-CNN model's confusion matrix which compares actual target values to those predicted by the machine learning model. The fisher rating CNN confusion matrix includes True Positive (T_P), True Negative (T_N), False Positive (F_P) and False Negative (F_N) values for non-cancerous cells (normal) and for three types of cervical cancer cells namely type 1, type 2, and type 3 as per this paper.

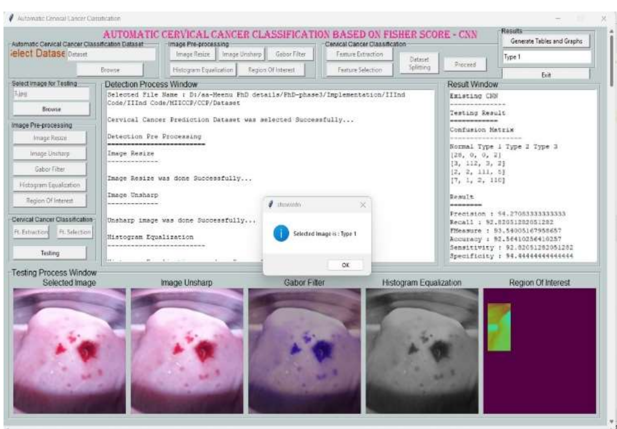

Figure 6: *Cervical cancer type classification in testing*

Sample output:

Figure 7 shows sample in console output with feature information and Figure 8 shows the metrics values that we use to check the performance as a graph for the proposed model. The performance of the proposed model is shown in Table I.

```
Feature Selection using Fisher Score Algorithm
-----------------------------------------------
Total no. of Features : 31
Selected Optimized Features : 27

Feature Names are...
--------------------
Energy
Sum Entropy
Maximum Probability
Skewness
Entropy
Information measure of Correlation2
Information Difference Normalized
Information measure of Correlation1
Sum Variance
Cluster Shade
Mean
Difference of Entropy
Kurtosis
Homogeneity
Sum of Average
Variance
Cluster Prominence
Sum of Entropy
Standard Deviation
```

Figure 7: *Console output*

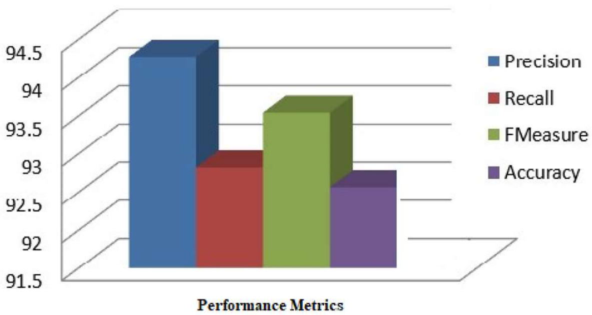

Figure 8: *Evaluation Metrics*

Method	Precision	Recall	F-Measure	Accuracy
FS-CNN	94.27083	92.82051	93.54005	92.5641

Table I. *Performance measure of the proposed method*

V. CONCLUSION

In the proposed model, a strategy for detecting and classifying cervical cancer using Fisher score with CNN was provided. To enhance categorization results, the image database is balanced using pre-processing techniques. The Fisher score-based Convolutional Neural Network (FSCNN) is currently used to classify cervical cancer on its own. Three distinct types of cervical cancer cells are employed for testing along with healthy (non-cancerous) cells. According to preliminary results, this procedure is reliable and effective, making it simpler to detect cervical cancer and resulting in an early diagnosis. The results show that the proposed

FSCNN classifier is 92.56% accurate in predicting cervical cancer. As an outcome, we may determine whether our intended work has improved over existing cervical cancer initiatives. This examination also shows the technology's advantages, such as its pace, readability and price. In future investigations, the proposed technique will be evaluated using more databases. Strong image processing technology and CNN algorithms might be used to construct a diagnosis system for newly formed cervical precancerous data.

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