Journal of Advanced Research in Applied Sciences and Engineering Technology 39, Issue 2 (2024) 19-36

SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage: https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Deep Neural Network for the Detection and Classification of Spontaneous Abortion Associated with Cervical Cancer

Priya Surendran Nair Anandavally[1,*], Vargheese Mary Amala Bai[2]

[1] Department of Computer Applications, Noorul Islam Centre for Higher Education (NICHE) Tamil Nadu, India
[2] Department of Information Technology, Noorul Islam Centre for Higher Education (NICHE) Tamil Nadu, India

ARTICLE INFO

Article history:
Received 5 September 2023
Received in revised form 23 November 2023
Accepted 12 January 2024
Available online 12 February 2024

Keywords:
Cervical cancer; Spontaneous abortion; Optimization; Deep neural network; Herlev; Multiclass classification

ABSTRACT

Cervical cancer is the most prevalent cancer and serious condition that currently poses a threat to the health of women. Automated cervical cancer diagnosis and classification from pap smear images has become essential due to the precision, dependency, and timely analysis of the cancer progression. The chance of occurrence of Spontaneous Abortion (SA) associated with cervical carcinoma can be identified from the pap smear image analysis. Advancements in Deep Neural Network (DNN) paved path to the efficient analysis of pap smear images for the detection of SA. The DNN must be optimized to obtain better accuracy in multiclass Herlev dataset pap smear image classification problem. The class *carcinoma-in-situ* is associated with SA and this class need to be identified without any error. For quantitative analysis of cell images, accurate localization of cell nuclei as well as the extraction of textural features are accomplished. Classification and decision-making are carried out as part of high-level processing to categorise the cancer phases into six classes. The domain aspects of cervical cancer are used to explore and present appropriate methods and techniques. This work focuses on the development of optimized DNN that can differentiate cancer classes in an efficient way. For Herlev images the proposed system provided multiclass average accuracy of 96.49%. Proposed EL-CNN architecture provided better outcomes than state-of-the-art systems.

1. Introduction

Cervical cancer is serious condition that currently poses a threat to the health of women due to the low survival rate. This takes several years to develop, but if identified in time, it might be curable. It is difficult for healthcare experts to determine the proper type of cervical cancer. Regular screening can enhance cervical cancer prognosis at an early stage and improve the survival rate. If cervical cancer is accurately detected early, the mortality rate of patients can be decreased [1]. Analysis of pap smear images is utilized to obtain the diagnosis. A pap smear test and visual examination with acetic acid are used to differentiate normal, precancerous, or cancerous cervical lesion. These tests find pre-neoplastic changes in cervical epithelial cells. It is a difficult and repetitive

* *Corresponding author.*
E-mail address: priyasaniche@gmail.com

https://doi.org/10.37934/araset.39.2.1936

task for a cytopathologist to visually analyse pap smear test results. In the case of cervical cancer detection, manual analysis took longer [2]. Due to image similarity, enormous readings and insufficient experience levels of pathologists, missed diagnoses and false diagnoses are frequently made.

For developing autonomous cervical cancer diagnosis, machine learning, and numerous computer vision/Deep Learning (DL) systems were implemented in earlier works. Current methods have drawbacks including being ineffective, inaccurate, and unable to generalise well, particularly in complex circumstances. Artificial intelligence models have been highlighted in a number of studies on cervical cancer. Despite recent scientific advances, there no effective treatment, especially when the disease is identified at advanced phase. Prevalence of cervical cancer has significantly decreased as a result of screening techniques like cytology and colposcopy [3]. A very helpful cell imaging-based detection technique for detecting cervical cancer is the pap smear. Cells must be identified as belonging to one of a variety of ordinal groups ranging from abnormal to normal.

The debate between manual screening and an automated system has persisted. The manual examination of cell images is time-consuming and laborious because pathologists must examine each image on a smeared slide under the microscope in order to diagnose a disease [4]. The screening of a mass population involves looking at a lot of samples, which takes time and calls for trained technicians. Medical imaging technology advancements have improved the quality of medical images, which has improved contributions to the early diagnosis of diseases. Commercial computer-assisted screening tools like the AutpPap300, PapNet, AutoCyte, Cytoanalyzer, CYBEST, etc. were created to automate the screening process, but the majority of these tools had drawbacks, such as a high rate of false-positive results, uncertainty about cost-effectiveness, and also a lack of consistency. Despite the existence of sophisticated automated systems for smear analysis, developing and middle-income nations with a high incidence and mortality rate of cervical cancer do not effectively use the automated systems due to their high cost and maintenance. Therefore, the creation of an affordable and efficient automated screening tool has grown into a significant research area that aids pathologists in the quick analysis and accurate diagnosis of samples.

The relationship between cervical cancer and Spontaneous Abortion (SA) is a complex one that is not fully understood. SA, also known as miscarriage, is the loss of pregnancy before 20 weeks of gestation. Some studies have found that women who have had multiple spontaneous abortions may be at slightly increased risk for cervical cancer. This association may be due to underlying health conditions or infections that increase the risk for both SA and cervical cancer. Studies have found that women with cervical infections caused by certain types of Human Papilloma Virus (HPV) are more likely to have spontaneous abortions and are also at increased risk for cervical cancer. Women who have had multiple SA may have higher rates of abnormal cervical cells; a condition known as Cervical Intraepithelial Neoplasia (CIN). CIN is a precancerous condition that can develop into cervical cancer if left untreated. These findings suggest that a history of cervical cancer may be a marker for an increased risk of SA.

There are several possible explanations for the association between SA and cervical cancer. One theory is that the hormonal changes that occur during pregnancy may affect the immune system and make it more susceptible to HPV infection. Additionally, the cervix may be more susceptible to infection during pregnancy due to increased blood flow and changes in cervical mucosa. Autoimmune disorders or chronic inflammatory conditions may be more likely to have spontaneous abortions and may also be at increased risk for cervical cancer. Additionally, it is clear if women who have had a cervical cancer are more likely to develop SA than women who have never had cervical cancer. It is recommended that women who have cervical cancer receive regular screenings, such as a pap test or HPV test, to detect any potential SA early. These screenings can detect abnormal cervical cells before they develop into cancer and can help prevent SA.

Deep Learning (DL) architecture encapsulates the non-linear relationship of the complex pattern and generates accurate predictions by using a large number of hidden layers. One of the popular DNN architectures with practical uses in image analysis and recognition is the Convolution Neural Network (CNN). Without relying on features extracted by humans, it is capable of learning features at various levels of abstraction and creates a system to learn all complex-level features like objects and shapes.

To increase the precision of classification, the idea of an automated method for detecting cervical cancer has been put forth by Wei *et al.,* [5]. Pre-processing was performed to lessen the effects of noise and irrelevant background on precise feature extraction that follows. Images were arranged in vertical orientation and GLCM was utilized to obtain the features from the texture. K-means clustering and the marker-controlled watershed were used to segment the image. Finally, 90% classification accuracy was achieved while recognising cervical cancer. For a dataset of 83 digitised histology images, a fusion oriented localized DL approach was investigated for categorizing Cervical Epithelial Neoplasia (CEN) grades by Mubarak *et al.,* [6]. For the classification of individual segments and the entire epithelium, features of DL patch were concatenated and utilized as next level's input. With an accuracy rate of 80.72%, this hybrid DL approach outperformed other imaging approaches individually by 15.51% and 11.66%, respectively.

In order to quantify cancer grades, Guo *et al.,* [7] introduced attention features calculated from epithelial region. Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) were used to investigate the voting fusion of vertical segments for image-based epithelium classification. Using leave-one-out, CIN classification training and testing can achieve an exact grade labelling accuracy of up to 88.5%. Gorantla *et al.,* [8] proposed a novel CervixNet methodology that improves the image of cervigrams, then segments the region of interest (RoI), classifies the RoI, and determines the best course of action. A brand-new Hierarchical Convolutional Mixture of Experts (HCME) scheme was suggested for the classification task. Given that small datasets are a problem that is inherent in the field of biomedical imaging, HCME is capable of addressing the issue of overfitting. By using Mobile-ODT and Intel dataset, this methodology yielded 96.54% categorization accuracy and 95.21% kappa score.

For the prediction of cancer type, Bijoy *et al.,* [9] proposed UNet-based segmentation technique. Using transfer learning, CNN model is trained to accurately predict the type of cervical cancer with 70% accuracy. Tomita *et al.,* [10] developed a DL technique for analysing high-resolution histological images for the detection of cervical carcinoma using tissue-level annotations with a mean accuracy of 83%. An area-oriented CNN method utilizing discriminatory pre-processing was suggested by Gautham *et al.,* [11]. To extract features from Herlev dataset, VGGNet architecture was used. Using Mask R-CNN and transfer learning, Allehaibi *et al.,* [12] presented a system for cervical cell image classification. Another CNN method for identifying nuclei from images was presented by Braz *et al.,* [13]. They created a CNN to assign to one of the three classes—cytoplasm, background, or nucleus. ISBI 2014 dataset was used for nucleus detection and produced precision value of 92.9%. A strong variational classification scheme involving pixel-wise CNN and optimized profile was presented by Tareef *et al.,* [14]. Classification was performed with precision, recall, and ZSI index of 94%, 95%, and 94%, respectively. Zhang *et al.,* [15] suggested an automated cervical nucleus classification method in light of this fact. This Fully CNN (FCNN) image area-based classification scheme avoids prior evaluation. Graph technique was suggested for fine segmentation that can locate the nucleus boundary as the most effective global solution.

Existing models have significant shortcomings in feature representation, feature extraction, and pathological classification. The limitations of these techniques included reduced performance accuracy, higher complexity in computing, higher dimensions of features, less reliability, and higher computational time as a result of insufficient hyperparameter optimization. An effective multiclass classification algorithm is proposed as a tool for computer-assisted disease diagnosis. Three levels of processing are necessary for the computational approach to be successful. The images are subjected to augmentation and region of interest enhancement in the first level, which is the initial level of processing. For quantitative analysis of cell images, accurate localization and segmentation of cell nuclei as well as the extraction of textural features are accomplished at the middle level of processing. Classification and decision-making are carried out as part of high-level processing to categorise the various disease phases into six classes.

2. Methodology
2.1 Dataset

Herlev pap smear database has been used in this experiment. This dataset was introduced by Herlev University Hospital and is available online [16]. It contains 6 classes and total 917 cell images. There are 3 normal classes and 3 abnormal classes. There are 242 normal images and 675 abnormal images. A 5-fold cross validation strategy was employed. This work utilized 80% of the images in the training iterations for fine tuning. Testing was done on the remaining 20%. All of the images were validated following 25 iterations. The average accuracy over five iterations was used to determine the final accuracy. The 5-fold cross-validation scheme was utilized for training and testing the deep CNN model on the Herlev dataset [17]. In Figure 1, examples of images from the Herlev dataset are displayed.

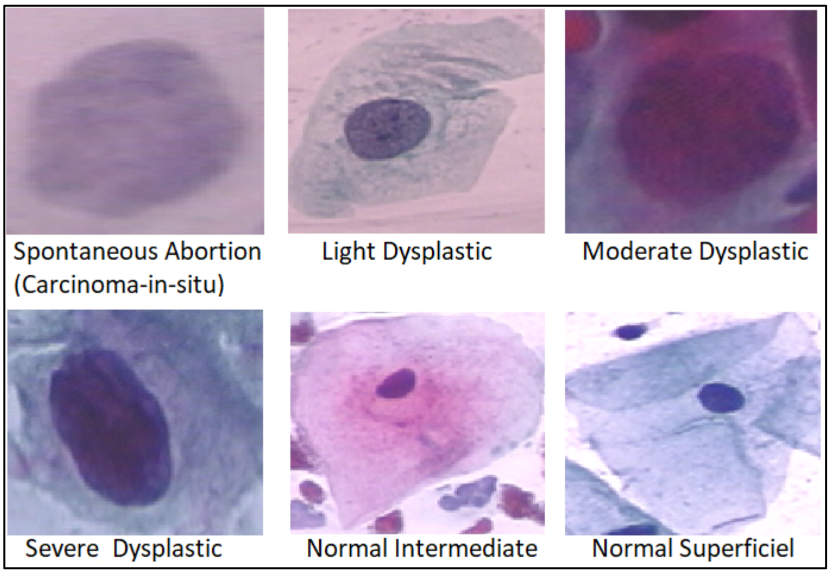

Fig. 1. Sample images from Herlev dataset

There are 3 stages of dysplastic cells: mild, moderate, and severe. Compared to severe dysplastic cells, a large percentage of moderate dysplastic cells will disappear without developing into malignant ones. The nuclei of squamous dysplastic cells are often bigger and darker, and they frequently stick together in clusters. The nuclei of cells with severe dysplasia are often enlarged, covered in black granules, and malformed [18]. According to cellular appearance, particularly as it relates to the nucleus, the cervical cells are grouped into 6 groups for analysis purpose. Table 1 provides an explanation of the distribution of different image classes in the enhanced dataset.

Table 1
Images in Herlev Dataset

Sl. No	Image Class	Total	Train	Test
1	Spontaneous Abortion (Carcinoma in situ)	600	494	106
2	Light Dysplastic	728	590	138
3	Moderate Dysplastic	584	458	126
4	Severe Dysplastic	788	619	169
5	Normal Intermediate	560	453	107
6	Normal Superficial	592	467	125

To increase accuracy and decrease error, the images in the dataset have been enhanced. Lack of enough datasets is the main barrier to applying DL to medical images. Patient privacy is one concern when using medical images. On the Internet, it might be challenging to directly get a certain dataset type. Data augmentation techniques are performed on a small dataset of cervical cancer cells. Since it is a tedious task to label huge number of diseases, highly qualified specialists are incorporated in the data collection process. Data augmentation can decrease overfitting of CNN with the dataset and increase the disease detection precision [19]. A parallel transpose operator is applied with 0.5 probability to update extraction in the initial state due to the nonlinearities in cervical cancer cell inversion. Since the nucleus size and intensity serve as a crucial criterion for differentiating between normal cervical cells and abnormal cells, there is no requirement for additional image augmentation techniques like warp and colour shifts [20]. The distribution of images in the dataset is depicted in Figure 2.

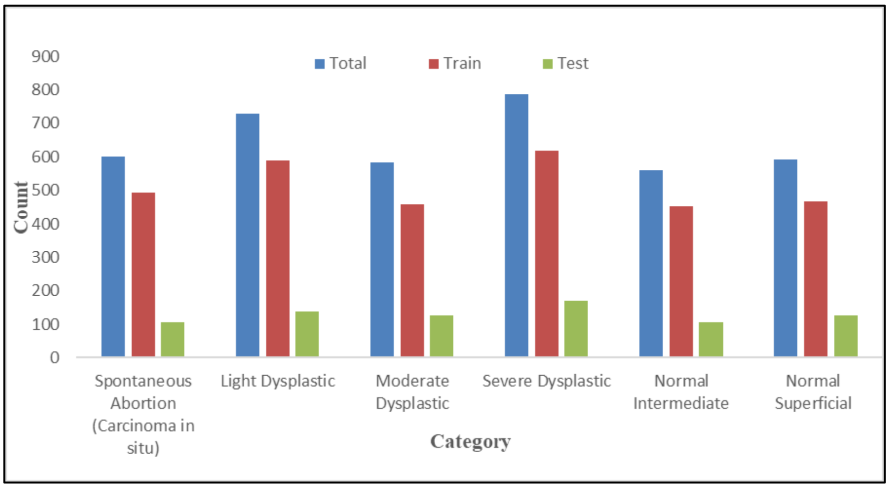

Fig. 2. Distribution of Various Categories in Dataset

2.2 Deep Learning Model

Medical image analysis is one of the numerous image analysis applications where Convolutional Neural Network (CNN) models have proved effective. This work suggests a cervical cancer categorization system based on CNNs that is primarily concerned with SA detection. It is exceedingly challenging to obtain a large dataset of medical images for the CNNs-based systems, which require enormous amounts of data for training [21]. Therefore, when the database size is small, extreme learning and fine tuning are common. A deep CNN framework is trained using a lot of images, and the trained model can be utilized as a benchmark model [22]. The parameters of the model are updated using the training set obtained from a specific dataset. The testing makes use of this refined model. Figure 3 displays a generic block diagram of the suggested system.

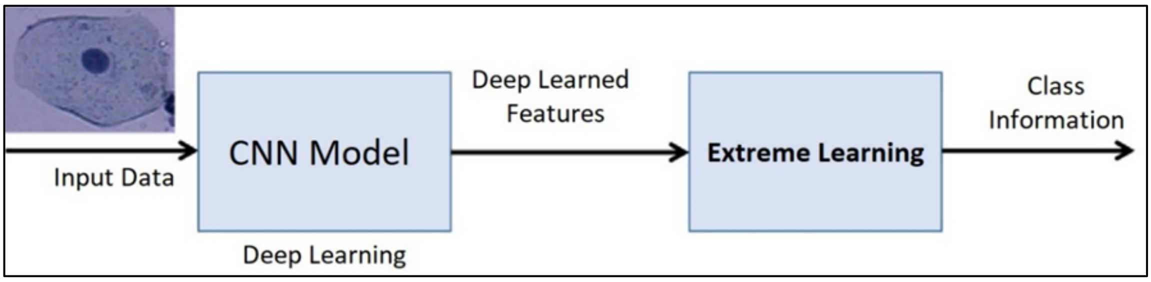

Fig. 3. Process Flow of Proposed Classification System

In the proposed approach, we examine EL based CNN model, which have deep architecture. Many convolutional layers and dense layers are present in the model. The RGB image with a size of 64 × 64 is the input. The first convolutional layer has 64 filters having dimension 5 x 5, while second convolutional layer comprises 128 filters having dimension 5 x 5. The filters have a 2-pixel stride. The max-pooling filter has a mask size of 2 x 2. The non-linear activation employs the ReLU operation. The attributes are flattened and placed into a fully linked layer following the max-pooling layer. A *softmax* (output) layer comes after two completely linked layers [23]. A training subset of the desired dataset was used to fine-tune the training once it had been completed. The model's parameters have been optimised using Adam algorithm. 0.01 is the optimum learning rate with a batch size of 20 and 25 epochs. Figure 4 depicts the proposed deep CNN model's design.

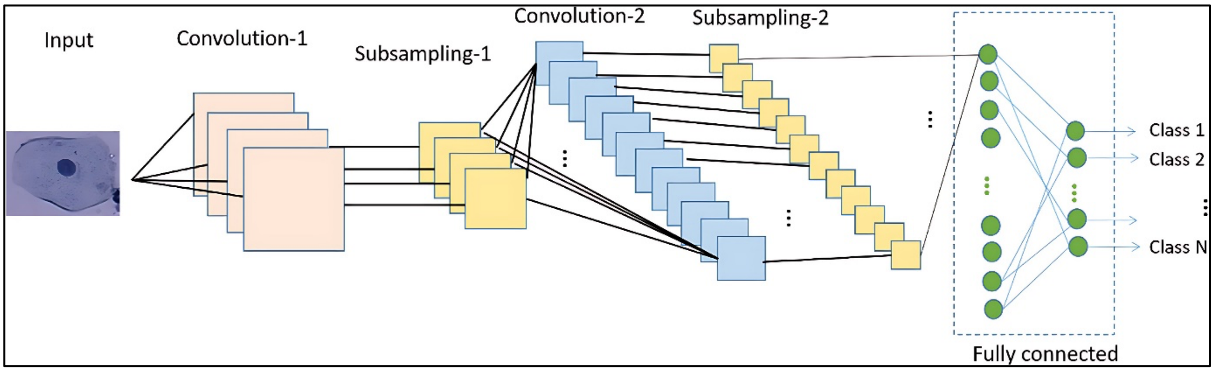

Fig. 4. Proposed Deep CNN Model

The convolution layer is created by taking the dot product of image pixels and filter values. Weights matrix generates the filter tensor. When the network uses backpropagation, the values in the filter matrix are updated. However, the programmer actively chooses the filter matrix's dimensions. The image will go to the pooling layer after passing through the first filter [24]. We can train the model more quickly since a pooling layer shrinks the size of the filter layer. Additionally, it avoids overfitting by removing undesirable values from the filter tensor. Max Pooling is a well-liked pooling technique. The procedure is similar to filtering, except the use of greatest value rather than the dot product. An activation function frequently employed in neural networks is the rectified linear unit (ReLu). The neural network is given non-linearity by using an activation function. As a result, we are able to address considerably more challenging issues because this network consists of only linear functions [25]. It would be a straight forward linear regression approach if we did not have an activation function in our network. Figure 5 displays the graphical representation of the proposed activation function (ReLu).

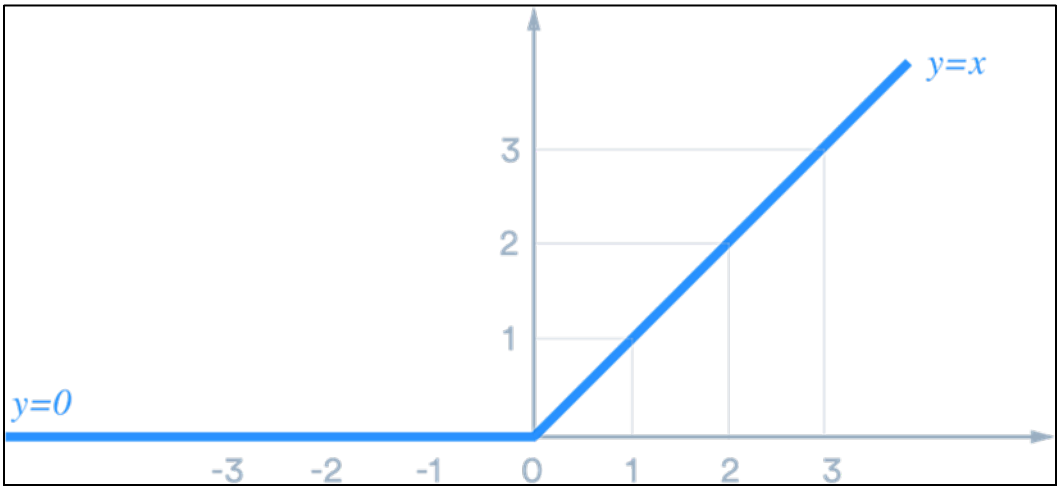

Fig. 5. ReLu Activation Function

An extension of logistic regression that can handle several classes is called *softmax* regression. The tag *y*(*i*) = {*1, 2, ..., C*} provides the output and *C* denote the count of all classes involved. For a trial input x, the algorithm obtains the proposition that estimate the probability P(y = k|x|) for all values of c = 1, 2, .., C. This algorithm provides a *C*-dimensional vector as output by generating C number of probabilities. *Softmax* intake vector z having dimension C. The output of *softmax* is a vector *y* with dimension *C* containing real values in the range [0, 1]. Eq. (1) defines this function as a normalised exponential.

$$y_c = \frac{e^{k(c)}}{\sum_{d=1}^{C} e^{k(d)}} \quad for\ c = 1, 2, 3, ..., C \tag{1}$$

The denominator $\sum_{d=1}^{c} e^{k(d)}$ perform the role of a regulator to ensure that the result follows the criteria mentioned in Eq. (2).

$$\sum_{c=1}^{C} y_c = 1 \tag{2}$$

It is possible to inscribe the probabilities generated by class *t* = *c* for *c* = 1, 2, 3, ..., *C* and input *k* using Eq. (3). The softmax function for multiclass classification is illustrated in Figure 6.

$$P = \frac{M}{\sum_{d=1}^{C} e^{k(d)}} \tag{3}$$

$$P = \begin{bmatrix} P(t=1 \mid k) \\ . \\ . \\ P(t=C \mid k) \end{bmatrix} \tag{4}$$

$$M = \begin{bmatrix} e^{k(1)} \\ . \\ . \\ e^{k(C)} \end{bmatrix} \tag{5}$$

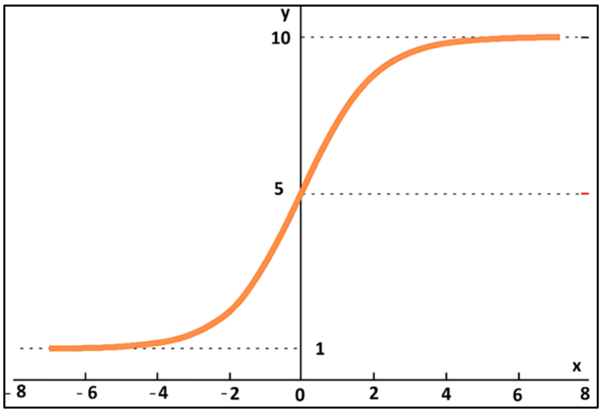

Fig. 6. Softmax Function

So, $P(t = c|k|)$ is the probability at which class c occurs for a particular input k. This research uses Extreme Learning (EL) for the optimization of classifier. EL is used in CNN to provide faster learning, easier convergence, and lower randomization. The output of EL give classes of Herlev dataset as output. The output of the first EL is deleted when it has done training, and the hidden layer is supplied to the second EL. Since the hidden layer's fixed number of neurons is 2048, this EL corresponds to a sparse interpretation [26]. The weights of the EL are optimised using the SGD algorithm. Assume that the ELM's hidden layer has N_h neurons. The layer's row-wise output vector is designated as $h(x_i)$, where x_i is the input vector, and has a size of 1 x N_h. The output weight vector, denoted as α, which joins the hidden layer to the output layer is N_h x N_o. Here N_o is the quantity of output classes. Eq. (6) defines the output EL.

$$f(x_i) = h(x_i)\beta, \quad i \in \{1 : N_h\} \tag{6}$$

The objective (loss) function is used to minimize the error in the network and it is defined in Eq. (7).

$$f_{loss} = \min \|\beta\|_g^2 + \delta \sum_{i=1}^{N_h} \|E_i\|^2 \tag{7}$$

Where, $||\beta||_g$ represents Frobenius norm of weight vector, δ represents penalty constrain, and the error vector during training is denoted as *E*. The process flow of EL based learning model is depicted in Figure 7.

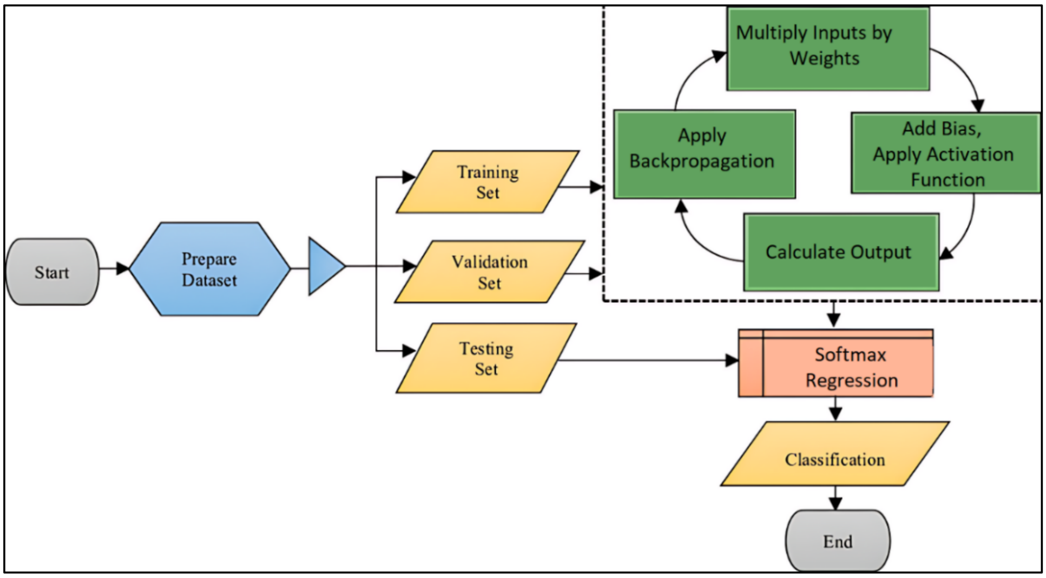

Fig. 7. Flow Chart of Proposed EL Scheme

In the Extreme Learning (EL) theory, the output weights are statistically calculated using the minimal average response of a linear system, whereas the input weights are produced at random in accordance with any continuous distribution function. Algorithm 1 describes a basic variant of the EL training process.

Algorithm 1: Basic EL Algorithm
Input: X=Dataset, T= Target, L= Hidden nodes.
Output: Parameters of EL.
Step 1: Randomly generate input weights (W) and bias (b).
Step 2: Calculate the hidden matrix, $H = (b + WX)G$
Step 3: Calculate the output weights, $b = T \oplus H$
Step 4: Return to the parameters of EL (β , *b* and *W*).
Step 5: Repeat step 1 to 4, until the EL parameters converge.

This work offers a CNN classifier based on EL to enhance the performance of simple EL model and fully utilise the potential. The detailed method mentioned in Algorithm 2 is made up of *M* separate CNN, and the final choice is calculated by merging the various results with a parameter set *F* discovered using an EL algorithm [27].

Algorithm 2: Proposed EL Classifier Training
Input: X=Dataset, T= Target, L= Hidden nodes, M= Models.
Output: Parameters of EL Classifier.
Step 1: *Initialize the value of* m=*1*, …….., *M*.
Step 2: Randomly generate input weights $W^{(m)}$ and bias $b^{(m)}$.
Step 3: Calculate the hidden matrix, $H = [b^{(m)} + W^{(m)} X]G$

Step 4: Calculate the output weights, $\beta^{(m)} = T \oplus H^{(m)}$
Step 5: Calculate the output, $Y^{(m)} = \beta^{(m)} H^{(m)}$
Step 6: Calculate the global hidden matrix, $H_g = \left[Y^{(1)}\, Y^{(2)} ....Y^{(M)} \right]$
Step 7: Calculate the fusion of parameters $F = T \oplus H_g$
Step 8: Return to the parameters of EL classifier ($\beta^{(m)}$, $b^{(m)}$ and $W^{(m)}$).
Step 9: Repeat step 2 to 8, until the EL classifier parameters converge.

Proposed EL-CNN model uses the first layer as its input layer. The next levels are convolutional, max pooling, dense, flatten, and fully connected layers. All of these layers are built on top of one another. Adam optimizer is used to get better classification outcomes. It functions well for problems with a lot of data or parameters. Hyper-parameters frequently have clear meanings and are simple to tune. To calculate the level of loss (error) that occurs throughout training and validation, Binary Cross Entropy (BCE) is used. Each projected probability is compared to the actual class output using BCE (6 classes). Then, a score is assigned to the probabilities according to how far they depart from the predicted value [28]. The parameters utilized in the model for the identification of SA and other kinds of cervical cancer are listed in Table 2.

Table 2
Proposed DCNN Model Summary

Layers	Type	Output Shape	Parameters
Input Layer	Dense	64 x 64 x 3	-
Convolution Layer	Conv2D	62 x 62 x 16	448
Max pooling layer	Maxpooling2D	31 x 31 x 16	0
Convolution Layer	Conv2D	29 x 29 x 32	4640
Convolution Layer	Conv2D	27 x 27 x 64	18496
Dense	Dense	27 x 27 x 64	4160
Dense	Dense	27 x 27 x 32	2080
Flatten	Flatten	23328	0
Dense	Dense	6	139974
Total			169,798
Trainable			169,798
Non-Trainable			0

Figure 8 shows the proposed DCNN model for Herlev dataset that initialize with 6 distinct classes. After the processing in convolutional, max pooling, dense, flatten and hidden layers, final output is generated with 6 classes and the prediction of individual classes [29]. In this model a batch size of 128 and 25 epochs were utilized for training and validation. 25 epochs were used because it is the best value at which the DCNN model converges and the loss and accuracy are stable providing best results.

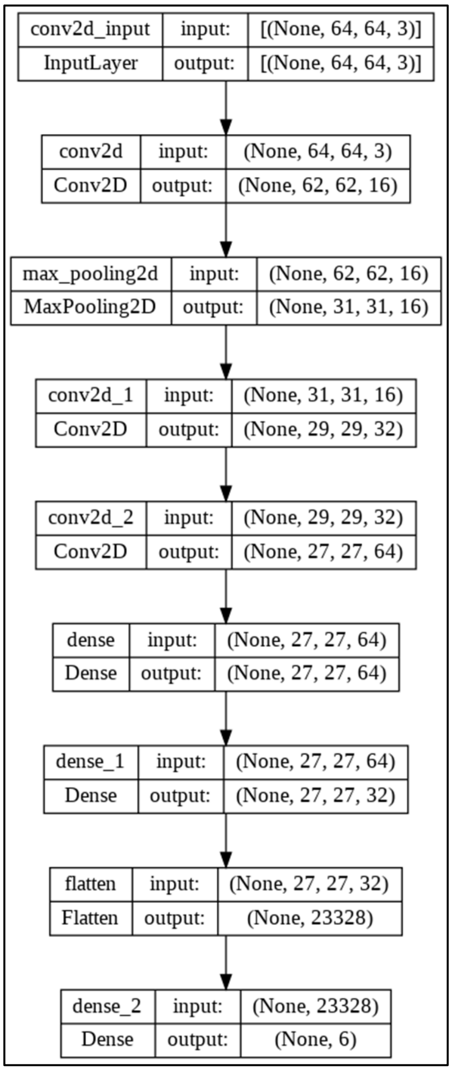

Fig. 8. Proposed DCNN Model

3. Results and Discussions

At the end of each epoch, training loss is the amount of error occurred in relation to the training data. The optimization procedure for training is to reduce loss. Therefore, the smaller the number, the better. Accuracy is defined as the proportion of accurate predictions to all other predictions made using the training data. The loss is typically, but not always, inversely related to accuracy. The validation counterpart has the same concepts as the training counterpart, but they are calculated using validation data rather than training data, the model cannot visualize them. The loss (*error*) [30] that happened during each epoch is obtained using the Categorical Cross Entropy (CCE). When there are two or more output labels in a multi-class classification model, CCE is utilised as the loss function. The output label receives multiple hot class encoder value in binary form. If output labels are represented in the form of integer, *keras* transforms it into category encoding using Eq. (8).

$$H_p(q) = -\frac{1}{N}\sum_{c=1}^{C}\sum_{i=1}^{N}\log P_{model}\left[y_i \in C_{y_i} \right] \tag{8}$$

In this calculation, the dual summation is performed over ‘*I*’ annotations, having count ‘N’, and ‘c’ classes with count C. The variable $y_i \in C_{y_i}$ is an indication of *i*th estimation fitting into *c*th class. $Pmodel[y_i \in C_{yi}]$denotes the probability by which *i*th estimation fit into *c*th class. It there exists more than 2 classes, the CNN produces a vector of "C" probabilities, where each value represents the likelihood that the CNN input should be categorised as falling under the corresponding category. When there are just two classes, the CNN only generates single probability y_i, the second being "1” minus output. This is why, although being a specific example of it, binary cross entropy differs slightly from CCE in appearance. During majority of the time, first-layer characteristics are too general to be used as exclusionary descriptions.

Figure 9 illustrates the convolutional layers' characteristics. As a consequence, we looked at features starting in the intermediate layers. One of these layers' outputs will suggest that the pap smear images were encoded with features. The succeeding classifier block will subsequently receive these attributes as input. The vast majority of extracted features can be mapped by *softmax* across the various CNN layers. The proposed classifier performed better overall in terms of differentiating power [31]. It has lately been discovered that connecting *softmax* as a last layer accelerates training.

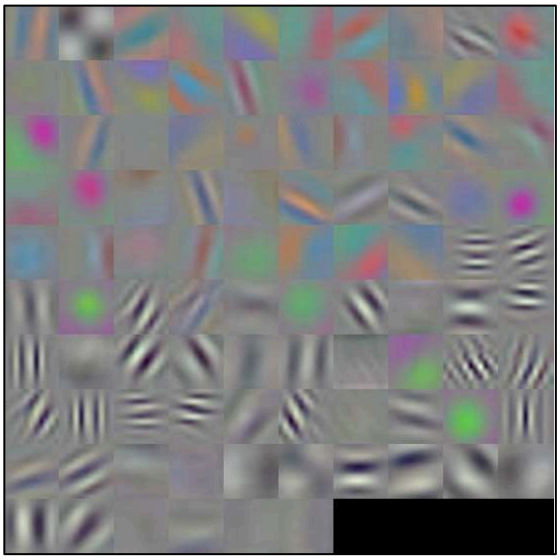

Fig. 9. Visualization of Convolutional Features

The purpose of this research is to assess the efficiency of CNN as a feature extractor and its efficacy in the detection situations on the provided dataset. It carefully selected and acquired features from various levels of the CNN. The research's primary concern is the fineness of the features that were derived from the CNN in terms of categorization effectiveness. Utilizing distinct layers from CNN, the features were accomplished. It is necessary to identify the optimum layer that would offer the greatest features distinguishing pap-smear cell images into different classes since the proposed EL- CNN was learned using the Herlev dataset.

In this EL approach, only deeper layers are taken into account, and the output features are utilized to train the classifier while the layers up to those layers are frozen. Although the number of trained entities is decreased by this technique, there are still a lot of features. For instance, the dimension of the produced feature set from third convolution layer (C3) is equivalent to 18496 features. We used a 70:30 split between training and testing in our training strategy. Additionally, we employed the same parameters by utilising cross-validation and fixed partitioning methodologies when comparing our findings to previous research. The pre-trained model based on EL is developed in Python and put through their paces on the Google Colab platform. $1x10^{-4}$ is the learning rate used in this work with a minimized batch size of 128 and 25 epochs. Reduction in learning rate improves the time required for training CNN. Over increment of learning rate causes training to get stuck at inappropriate results. Training and validation performance of proposed EL-CNN classifier is depicted in Figure 10. To validate the effectiveness and efficiency of proposed EL-CNN model, 4 metrics are computed. The metrics are accuracy, recall, precision and F1-score. To define these metrics False Positive (FP), False Negative (FN), True Negative (TN) and True Positive (TP) are employed.

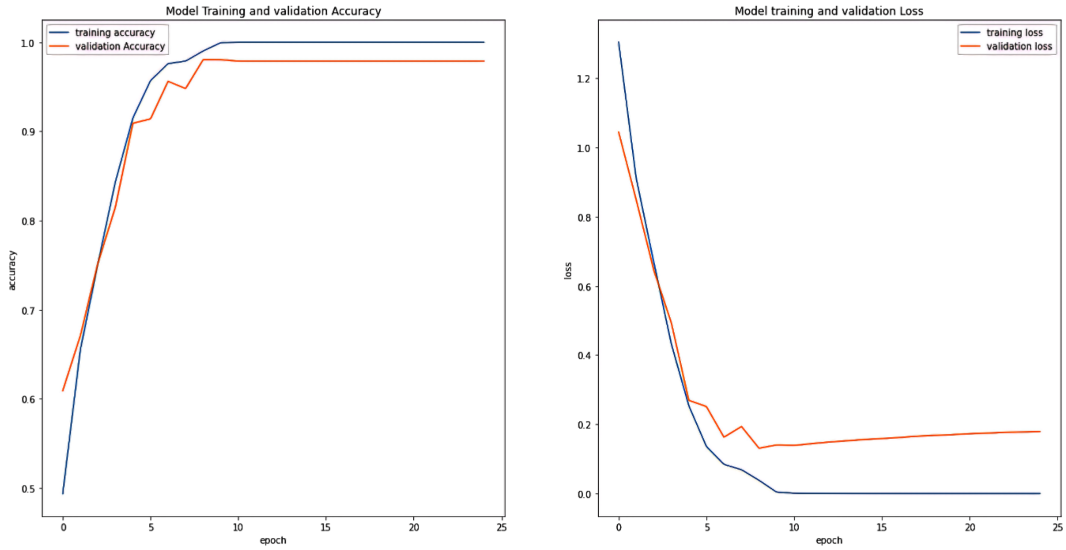

Fig. 10. Training and Validation Performance of Proposed Classifier

The performance parameters are expressed mathematically as,

$$Precision = \frac{TP}{FP + TP} \tag{9}$$

$$Recall = \frac{TP}{FN + TP} \tag{10}$$

$$Accuracy = \frac{TN + TP}{FN + TN + FP + TP} \tag{11}$$

$$F1 - Score = \frac{2 \times TP}{FN + FP + 2TP} \tag{12}$$

After the 10th epoch, performance parameter values are constant and high. This is because an EL technique was used to tackle the categorization problem. During training, there is a possibility that an error can happen, that can be considered as loss. The loss in the suggested EL-CNN model for classifying cervical cancer is just 0.2, which is very low. The evaluation has made use of the whole collection of test images. The mean accuracy of the proposed EL-CNN model is 96.49%. The mean percentages for precision, recall, and F1-score are 97.43%, 96.13%, and 97.32%, respectively. To improve the classification performance, the number of pap smear images utilised for training might be increased. Table 3 presents the classification report produced for the suggested multiclass classification model. Prime motive of this research is to identify the chance of SA y analysing the severity of cervical cancer. The proposed EL-CNN model is efficient in identifying SA class with 100% accuracy. Minimum accuracy of 94% is obtained for light dysplastic and severe dysplastic classes. Maximum value of precision is 99% which is obtained for SA class. Minimum value of precision is 95% which is obtained for light dysplastic and severe dysplastic classes. Maximum value of recall is 100% which is obtained for SA class. Minimum value of recall is 91% which is obtained for light dysplastic class. Maximum value of F1-score is 100% which is obtained for SA class. Minimum value of F1-score is 93% which is obtained for light dysplastic class.

Table 3
Classification Report

Category	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)	Support
light dysplastic	95	91	93	94	138
moderate dysplastic	96	98	97	97	126
normal intermediate	97	93	95	97	107
normal superficial	97	98	97	97	125
severe dysplastic	95	99	97	94	169
spontaneous abortion	99	100	100	100	106

From the classification report, it can be inferred that, SA class provides better performance compared to other cervical cancer classes. The proposed EL-CNN model is efficient in identifying SA class from the pap smear dataset. The performance of individual classes is illustrated in Figure 11.

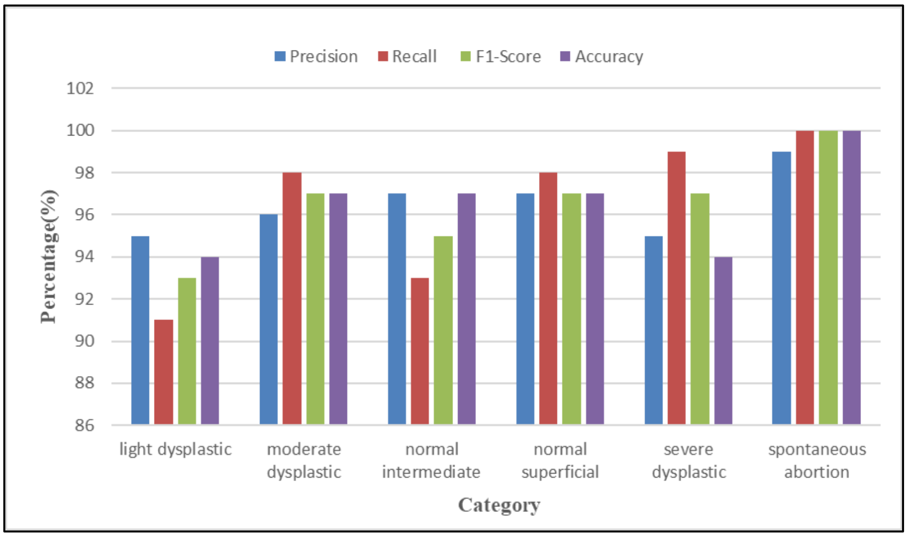

Fig. 11. Category wise classification performance

To assess the efficiency of the developed EL-CNN method, a detailed comparison of classification performance is required. On various datasets, the proposed transferred models' classification performance is evaluated. Table 4 compares the efficiency of existing models using the selected performance metrics.

Table 4
Comparison of Cervical Cancer Classification Models

Model	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
AlexNet	94.92	95.21	94.78	95.03
GoogleNet	87.73	88.09	85.56	89.31
ResNet 50	91.16	90.58	91.57	91.65
VGG16	93.37	93.62	92.87	93.24
Inception v3	88.92	85.06	86.74	86.81
Inception ResNet v2	88.95	88.40	90.57	89.92
EL-CNN (Proposed)	97.43	96.13	97.32	96.49

When comparing classification accuracy, the EL-CNN model has the best score of 96.49%. Pre-trained models with high accuracy rates were VGG16 (93.24%), ResNet101 (91.65%) and AlexNet (95.03%). The accuracy of the proposed EL-CNN is 1.46% higher than that of AlexNet. EL-CNN outperforms all other classifiers in terms of precision by providing 97.43%. Precision of 94.92% was achieved by AlexNet, 91.16% by ResNet101, and 93.37% by VGG16. The precision of EL-CNN is 2.51% higher than that of AlexNet. Recall value for EL-CNN is 96.13%. This model has the highest recall value when measured against other models. Recall rates for VGG16 were 93.62%, 95.21% for Inception ResNet v2, and 95.21% for AlexNet. The recall of the El-CNN is 0.92% higher than AlexNet's recall. When compared, EL-CNN has the greatest F1-score. The AlexNet model has a 94.78% F1-score, compared to 97.32% of EL-CNN model. There is a disparity of 3.46% between these two methods. EL-CNN has the highest F1-Score for SA detection and cervical cancer categorization. The importance of particular parameters emphasizes the contribution of EL in lowering overfitting and increasing classification accuracy. It is discovered that the suggested model and AlexNet are in capable of locating samples across significant datasets. Figure 12 compares EL-CNN's performance with cutting-edge cervical cancer classifiers.

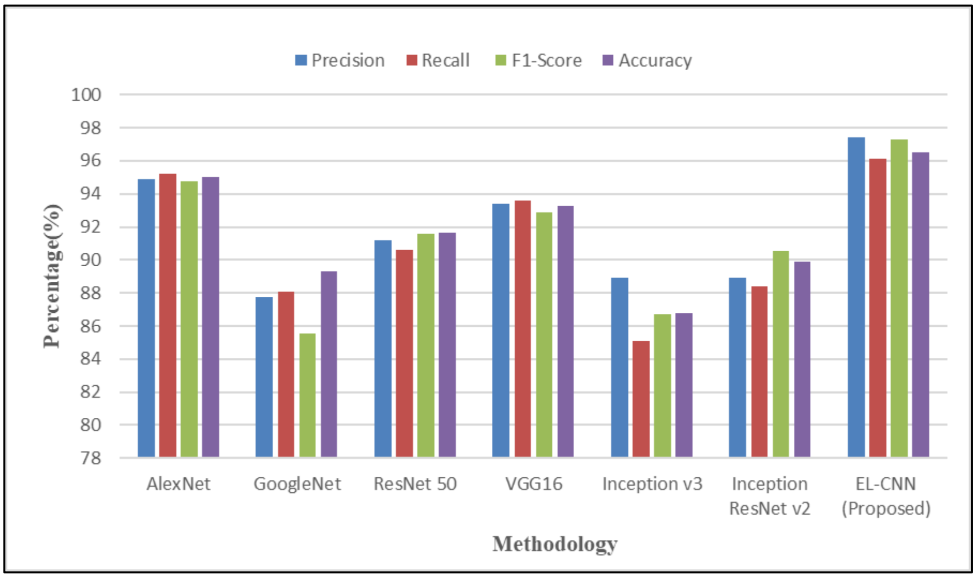

Fig. 12. Comparison of Classification Performance

The fundamental driving force behind EL-CNN based models is the fact that hundreds of labelled datasets are utilised to solve really challenging issues with them. Years of data collecting are required in order to build a dataset for deep learning models. Using EL-based CNN systems with a big dataset for classification has a number of benefits. The categorising mechanism is completely automated, first and foremost. Second, no longer are feature extraction, noise filtering, ROI delineation, and selection necessary. Thirdly, the EL-CNN models' predictions are reproducible and free of bias. Finally, a ceiling degree of accuracy is attained, which is different from earlier DCNN approaches. The usage of GPU in Google Colab framework as hardware shortens the calculation period. It took 3 m and 42 s to train EL-CNN on Herlev dataset. The proposed model is capable of detecting SA cases with 100% accuracy, which satisfies the prime objective of the research. The performance metrics of proposed multiclass classifier is higher than existing models. Sample predictions and ground truth are illustrated in Figure 13.

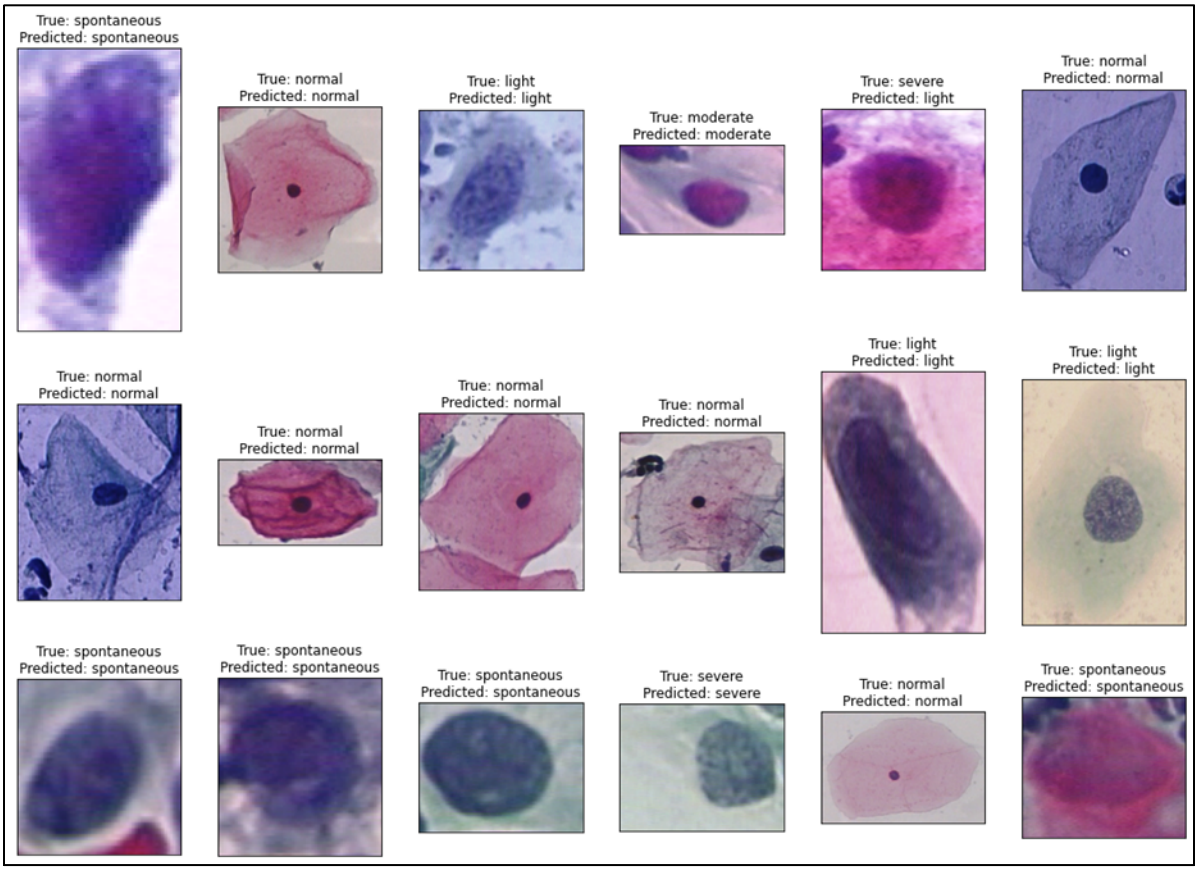

Fig. 13. Ground truth and prediction results

4. Conclusions

This work investigated several pre-trained CNN methods along with EL-CNN for the detection of SA and classification of pap smear images. The technique of concatenating CNN structures with EL is efficient in attaining peak rate of recognition. EL-CNN outperformed other classifiers by attaining accuracy of 96.49%, precision of 97.43%, recall of 96.13% and F1-score of 97.32% with Herlev dataset. EL-CNN deliver highest prediction accuracy, that has been achieved through optimization. EL-CNN has 100% accuracy in identifying SA instances. In terms of eliminating the requirement for pre-processing stages, it performs superior to existing techniques. Furthermore, when compared to proposed EL-CNN, the pre-trained AlexNet classifier provided poorer performance metrics. Future study will concentrate on putting the models into mobile platforms, reducing computing complexity, and investigating additional methods of fine-tuning.

Acknowledgement

This research was not funded by any grant.

References

[1] Shanthi, P. B., K. S. Hareesha, and Ranjini Kudva. "Automated detection and classification of cervical cancer using pap smear microscopic images: A comprehensive review and future perspectives." *Engineered Science* 19 (2022): 20-41.

[2] William, Wasswa, Andrew Ware, Annabella Habinka Basaza-Ejiri, and Johnes Obungoloch. "A review of image analysis and machine learning techniques for automated cervical cancer screening from pap-smear images." *Computer methods and programs in biomedicine* 164 (2018): 15-22. https://doi.org/10.1016/j.cmpb.2018.05.034

[3] William, Wasswa, Andrew Ware, Annabella Habinka Basaza-Ejiri, and Johnes Obungoloch. "A review of image analysis and machine learning techniques for automated cervical cancer screening from pap-smear images." *Computer methods and programs in biomedicine* 164 (2018): 15-22. https://doi.org/10.1016/j.cmpb.2018.05.034

[4] Desiani, Anita, Bambang Suprihatin, Sugandi Yahdin, Ajeng I. Putri, and Fathur R. Husein. "Bi-path Architecture of CNN Segmentation and Classification Method for Cervical Cancer Disorders Based on Pap-smear Images." *IAENG International Journal of Computer Science* 48, no. 3 (2021).

[5] Wei, Lisheng, Quan Gan, and Tao Ji. "Cervical cancer histology image identification method based on texture and lesion area features." *Computer Assisted Surgery* 22, no. sup1 (2017): 186-199. https://doi.org/10.1080/24699322.2017.1389397

[6] AlMubarak, Haidar A., Joe Stanley, Peng Guo, Rodney Long, Sameer Antani, George Thoma, Rosemary Zuna, Shelliane Frazier, and William Stoecker. "A hybrid deep learning and handcrafted feature approach for cervical cancer digital histology image classification." *International Journal of Healthcare Information Systems and Informatics (IJHISI)* 14, no. 2 (2019): 66-87. https://doi.org/10.4018/IJHISI.2019040105

[7] Guo, Peng, Koyel Banerjee, R. Joe Stanley, Rodney Long, Sameer Antani, George Thoma, Rosemary Zuna, Shelliane R. Frazier, Randy H. Moss, and William V. Stoecker. "Nuclei-based features for uterine cervical cancer histology image analysis with fusion-based classification." *IEEE journal of biomedical and health informatics* 20, no. 6 (2015): 1595-1607. https://doi.org/10.1109/JBHI.2015.2483318

[8] Gorantla, Rohan, Rajeev Kumar Singh, Rohan Pandey, and Mayank Jain. "Cervical cancer diagnosis using cervixnet-a deep learning approach." In *2019 IEEE 19th international conference on bioinformatics and bioengineering (BIBE)*, pp. 397-404. IEEE, 2019. https://doi.org/10.1109/BIBE.2019.00078

[9] Bijoy, M. B., A. Ansal Muhammed, and P. B. Jayaraj. "Segmentation based preprocessing techniques for predicting the cervix type using neural networks." In *Computational Vision and Bio-Inspired Computing: ICCVBIC 2019*, pp. 717-726. Springer International Publishing, 2020. https://doi.org/10.1007/978-3-030-37218-7_81

[10] Tomita, Naofumi, Behnaz Abdollahi, Jason Wei, Bing Ren, Arief Suriawinata, and Saeed Hassanpour. "Attention-based deep neural networks for detection of cancerous and precancerous esophagus tissue on histopathological slides." *JAMA network open* 2, no. 11 (2019): e1914645-e1914645. https://doi.org/10.1001/jamanetworkopen.2019.14645

[11] Gautam, Srishti, Arnav Bhavsar, Anil K. Sao, and K. K. Harinarayan. "CNN based segmentation of nuclei in PAP-smear images with selective pre-processing." In *Medical Imaging 2018: Digital Pathology*, vol. 10581, pp. 246-254. SPIE, 2018. https://doi.org/10.1117/12.2293526

[12] Allehaibi, Khalid Hamed S., Lukito Edi Nugroho, Lutfan Lazuardi, Anton Satria Prabuwono, and Teddy Mantoro. "Segmentation and classification of cervical cells using deep learning." *IEEE Access* 7 (2019): 116925-116941. https://doi.org/10.1109/ACCESS.2019.2936017

[13] Braz, Eliezer Farrant, and Roberto De Alencar Lotufo. "Nuclei detection using deep learning." *Proc. Simpósio Brasileiro Telecomunicações Processamento Sinais* (2017): 1059-1063. https://doi.org/10.14209/sbrt.2017.48

[14] Tareef, Afaf, Yang Song, Heng Huang, Yue Wang, Dagan Feng, Mei Chen, and Weidong Cai. "Optimizing the cervix cytological examination based on deep learning and dynamic shape modeling." *Neurocomputing* 248 (2017): 28-40. https://doi.org/10.1016/j.neucom.2017.01.093

[15] Zhang, Ling, Milan Sonka, Le Lu, Ronald M. Summers, and Jianhua Yao. "Combining fully convolutional networks and graph-based approach for automated segmentation of cervical cell nuclei." In *2017 IEEE 14th international symposium on biomedical imaging (ISBI 2017)*, pp. 406-409. IEEE, 2017. https://doi.org/10.1109/ISBI.2017.7950548

[16] http://fuzzy.iau.dtu.dk/download/smear2005

[17] Chankong, Thanatip, Nipon Theera-Umpon, and Sansanee Auephanwiriyakul. "Automatic cervical cell segmentation and classification in Pap smears." *Computer methods and programs in biomedicine* 113, no. 2 (2014): 539-556. https://doi.org/10.1016/j.cmpb.2013.12.012

[18] Bhatt, Anant R., Amit Ganatra, and Ketan Kotecha. "Cervical cancer detection in pap smear whole slide images using convnet with transfer learning and progressive resizing." *PeerJ Computer Science* 7 (2021): e348. https://doi.org/10.7717/peerj-cs.348
[19] Dong, Na, Li Zhao, Chun-Ho Wu, and Jian-Fang Chang. "Inception v3 based cervical cell classification combined with artificially extracted features." *Applied Soft Computing* 93 (2020): 106311. https://doi.org/10.1016/j.asoc.2020.106311
[20] Win, Kyi Pyar, Yuttana Kitjaidure, Kazuhiko Hamamoto, and Thet Myo Aung. "Computer-assisted screening for cervical cancer using digital image processing of pap smear images." *Applied Sciences* 10, no. 5 (2020): 1800. https://doi.org/10.3390/app10051800
[21] Cheng, Junlong, Shengwei Tian, Long Yu, Hongchun Lu, and Xiaoyi Lv. "Fully convolutional attention network for biomedical image segmentation." *Artificial Intelligence in Medicine* 107 (2020): 101899. https://doi.org/10.1016/j.artmed.2020.101899
[22] Lin, Haoming, Yuyang Hu, Siping Chen, Jianhua Yao, and Ling Zhang. "Fine-grained classification of cervical cells using morphological and appearance based convolutional neural networks." *IEEE Access* 7 (2019): 71541-71549. https://doi.org/10.1109/ACCESS.2019.2919390
[23] Xue, Dan, Xiaomin Zhou, Chen Li, Yudong Yao, Md Mamunur Rahaman, Jinghua Zhang, Hao Chen, Jinpeng Zhang, Shouliang Qi, and Hongzan Sun. "An application of transfer learning and ensemble learning techniques for cervical histopathology image classification." *IEEE Access* 8 (2020): 104603-104618. https://doi.org/10.1109/ACCESS.2020.2999816
[24] Chen, Wen, Xinyu Li, Liang Gao, and Weiming Shen. "Improving computer-aided cervical cells classification using transfer learning based snapshot ensemble." *Applied Sciences* 10, no. 20 (2020): 7292. https://doi.org/10.3390/app10207292
[25] Hussain, Elima, Lipi B. Mahanta, Chandana Ray Das, Manjula Choudhury, and Manish Chowdhury. "A shape context fully convolutional neural network for segmentation and classification of cervical nuclei in Pap smear images." *Artificial Intelligence in Medicine* 107 (2020): 101897. https://doi.org/10.1016/j.artmed.2020.101897
[26] Gautam, Srishti, Arnav Bhavsar, Anil K. Sao, and K. K. Harinarayan. "CNN based segmentation of nuclei in PAP-smear images with selective pre-processing." In *Medical Imaging 2018: Digital Pathology*, vol. 10581, pp. 246-254. SPIE, 2018. https://doi.org/10.1117/12.2293526
[27] Karim Kutty, Sabeena, and Gopakumar Chandrasekhara Menon. "Enhancing convolutional neural network model with spectral features for the identification of cervical dysplasia." *International Journal of Imaging Systems and Technology* 32, no. 6 (2022): 1916-1927. https://doi.org/10.1002/ima.22740
[28] Fang, Ming, Xiujuan Lei, Bo Liao, and Fang-Xiang Wu. "A Deep Neural Network for Cervical Cell Classification Based on Cytology Images." *IEEE Access* 10 (2022): 130968-130980. https://doi.org/10.1109/ACCESS.2022.3230280
[29] Archana, M. C. P., and J. Vinitha Panicker. "Deep convolutional neural networks for multiclass cervical cell classification." In *2022 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)*, pp. 376-380. IEEE, 2022. https://doi.org/10.1109/WiSPNET54241.2022.9767129
[30] Ramli, S. S., H. Mohamad Nor, N. S. Saharizan, and M. A. Salim Nasir. "Cubic Bezier homotopy function for solving exponential equations." *Journal of Advanced Research in Computing and Applications* 4, no. 1 (2016): 1-8.
[31] Letchumanan, L. Thiruvarasu, Noordin Mohd Yusof, Hamed Gholami, and Nor Hasrul Akhmal Bin Ngadiman. "Green Lean Six Sigma: A Review." *Journal of Advanced Research in Technology and Innovation Management* 1, no. 1 (2021): 33-40.

Name of Author	Email
Priya Surendran Nair Anandavally	priyasaniche@gmail.com
Dr. Vargheese Mary Amala Bai	mamalas@gmail.com