

# Detection of Cervical Cancer Using Deep Transfer Learning

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## Abstract

*Cervical cancer, the fourth most prevalent disease among females, is one of the major threats to the health of women worldwide. The early detection of cervical cancer is crucial for efficient disease management and medical care since it increases the likelihood of treating and curing the disease. Medically cervical cancer is usually diagnosed using pap test or colposcopic examination. These tests are time consuming and lack of enough, but with technological advancement and application of artificial intelligence to health care, machine learning algorithms has been giving faster and more accurate prediction of illness. This study made use of the readily available SIPAKMed dataset which includes the collection of a large image dataset of 4049 images. Due to the fact that detection of this type of cancer using medical images gives a faster and more accurate detection compared to using structured dataset comprising of various attributes related to cervical cancer. Pretrained EfficientNet-B7 was used as the detection model. The dataset went through series of preprocessing techniques like filtering using low and high pass filter, normalization using Min-Max Scalar. Label and image data were then converted to an array. The developed system was evaluated and gave an average accuracy and precision of 87% and 87% respectively, it was then compared with Graph Neural Network and Random Forest but they were both outperformed. As a result of this, EfficientNet-B7 is a very good deep learning algorithm for detecting cervical cancer using medical images. Other architectures of convolutional neural networks should be experimented and their performance should be compared with the developed system in future work, while larger dataset should be utilized as well.*

**Keywords:** Convolutional neural networks, EfficientNet B7, Cervical cancer, Medical imaging, Transfer Learning.

## INTRODUCTION

Cervical cancer is the world's fourth most common malignant disease in women. Sub-Saharan Africa has the highest rates of cervical cancer in the world, largely attributed to low cervical cancer screening coverage (Pimple and Mishra, 2022). Cervical cancer is a preventable disease. Yet it is the most common cause of cancer in the African Region where it accounts for 22% of all female cancers and 12% of all newly diagnosed cancer in both men and women every year (World Health Organization, 2015). In Africa, 34 out of every 100 000 women are diagnosed with cervical cancer and 23 out of every 100 000 women die from cervical cancer every year (Africa Health Organization, 2020). Cancer is a group of diseases involving abnormal cell growth with the potential to invade or spread to other parts of the body. Cervical cancer is a type of cancer that occurs in the cells of the cervix – the lower part of the uterus that connects to the vagina (MayoClinic, 2022). Many factors, such as the human papillomavirus and sexually transmitted diseases, increase the risk of developing cervical cancer as well as

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smoking. Identifying those factors and developing a classification model to determine whether the cases are cervical cancer is difficult (Zhang *et al.*, 2020).

Detection of cervical cancer is usually done by physical examination of the cervix, diagnosing through manual cross examination on Magnetic Resonance Imaging/Computer Tomography (MRI/CT) scans, Pap test and colposcopic examination. This might be time consuming and non-availability of enough medical practitioners with specialization in this area might be challenging. The availability of electronic medical records has made medical prediction easier, with the use of patient historical data, future occurrence can be predicted ahead of time. As a result of this, employing machine learning approach to detect cervical cancer in MRI will help in earlier, faster and more accurate detection of the cancer and in turn help medical doctors to perform their diagnosis faster and begin treatment plan earlier (Al Mudawi and Alazeb, 2022). Convolutional neural networks (CNN) have been proven to be a good deep learning algorithm for image classification due to its good performance on many medical image classifications. CNN is designed to process data with grid pattern or structured array of data like images, which has its basis from the formation and arrangement of animal visual cortex (Soladoye, 2023). It comprises of building blocks like convolution layers, pooling layers, and fully connected layers. The convolution layer is the basic part of the CNN which is in charge of feature extraction from the input data, which is the combination of both linear (Convolution operation) and non-linear operations (activation function). The pooling layer is the layer where the dimension of the features extracted by the convolution layer is reduced in order to reduce the size and number of the subsequent parameters that can be learnt (Nisha and Meeral, 2021). EfficientNet B7 is a CNN based pre trained model on ImageNet-1k, with these images having a resolution of 600x600. The baseline model of the architecture is B0 designed by AutoML MNAS, this EfficientNet-B7 was obtained through the scaling up of the baseline EfficientNet-B0 (Khalil *et al.*, 2022).

Section 2 of this research article presents some theoretical background and a review of some selected and relevant related works. The methodology employed was discussed in Section 3, while the evaluation result of the system was discussed in section 4. Section 5 concludes the paper with highlight of the major finding and recommendation for future work.

Cervical cancer typically develops slowly over many years, beginning with pre-cancerous changes in cervix cells that can be detected through regular cervical cancer screenings, such as a Pap test or HPV test. These precancerous changes are frequently treatable before they progress to cancer. If left untreated, cervical cancer can spread to other parts of the body, including the bladder, rectum, and lungs, and can be fatal. Depending on the stage and location of the cancer, the main treatments for cervical cancer include surgery, radiation therapy, and chemotherapy. Early detection and diagnosis of cervical cancer can improve patient survival significantly (Zhang *et al.*, 2020).

Staging characterises or categorises cancer depending on how much cancer is present in the body and where it is at the time of diagnosis, as shown in Figure 1, different stages shows the severity of this cancer based on their stages. Some of the Cervical Cancer signs and symptoms are abnormal vagina bleeding, unusual vagina discharge, early menopause, narrowing of the vagina and Lymphoedema (Obermair, 2017).

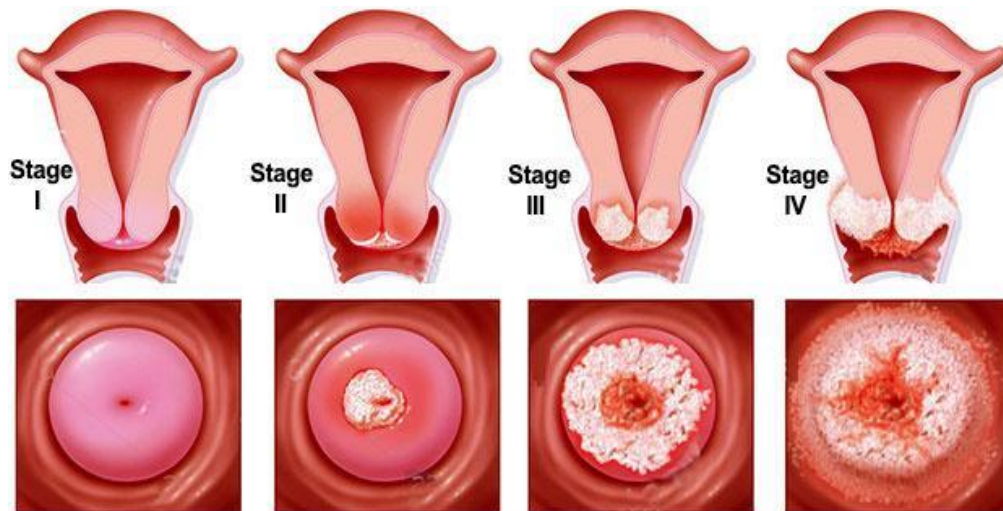


Figure 1: Stages of Cervical Cancer (Obermair, 2017)

Many researches have been done on the detection of cervical cancer using various machine learning techniques. These studies are reviewed to understand the state of art in the research area and identify possible gaps to fill with the research.

Alsubai, Alqahtani and Sha (2023) proposed a Privacy Preserved Cervical Cancer Detection Using Convolutional Neural Networks Applied to Pap Smear Images using the publicly available SIPaKMeD dataset having five cell categories: superficial-intermediate, parabasal, koilocytotic, metaplastic, and dyskeratotic. Pap smear images were segmented, and a deep CNN using four convolutional layers was applied to the augmented images of cervical cells obtained from Pap smear slides. The system gave a good performance when evaluated, however, the system was not tested on a large dataset of real-world Pap smear images. Glučina, Lorencin, and Anđelić (2023) conducted a study for Cervical Cancer Diagnostics Using Machine Learning Algorithms and Class Balancing Techniques. In the research, publicly available cervical cancer data collected on 859 female patients are used. Each sample consists of 36 input attributes and four different outputs: Hinselmann, Schiller, cytology, and biopsy. Due to the significant unbalance of the data set, some data oversampling techniques were applied, after which traditional machine learning algorithms were used for the classification. Al Mudawi and Alazeb (2022) proposed a ML-based approach to predict cervical cancer with a focus on data pre-processing, predictive model selection, and computational complexity analysis. Series of pre-processing techniques were employed to ensure the dataset is in good format. Traditional machine learning algorithms like Random Forest, decision tree, adaptive boosting, and gradient boosting algorithms and Support vector machine were used as the classifiers, with the first four algorithms giving best performance followed by SVM.

Lilhore *et al.*, (2022) proposed a hybrid model for detecting cervical cancer that combines causal analysis and machine learning techniques. The model utilised a causal Bayesian network (CBN) to identify the most relevant factors associated with cervical cancer and a random forest classifier to predict the likelihood of cervical cancer and outperformed other machine learning models such as support vector machines, k-nearest neighbour, and decision trees when evaluated. Karuparthi and Abishek (2022) conducted a similar study where they explored the use of data mining techniques such as the Support Vector Algorithm and Random Forest Algorithm to predict cervical cancer indications using the biopsy test. It focuses on the use of the Random Forest Algorithm (RF) to deal with imbalanced medical data

sets. The CART technique and feature randomness produced a better model than individual constituent models. Surendiran, Balaji and Deepa (2022) examined the use of Deep Learning and Machine Learning techniques to classify cervical cytopathology images and discussed common deep-learning architectures. The study highlights the need for more complex models to improve accuracy, as most proposed approaches have been applied to the same dataset. The review provides valuable insights for researchers in the field to build upon existing work. Chadaga *et al.* (2022) designed a computer-aided diagnostic method to screen cervical cancer patients using a custom stacked ensemble machine learning approach. The research conducted a deep exploratory analysis and utilised techniques for feature selection and imbalanced data. It also highlights risk factors such as long-term use of hormonal contraceptives and age and the role of IUDs in decreasing the likelihood of contracting cervical cancer. The final model achieved high accuracy, precision, recall, F1-score, AUC, and average precision. Abdelrahman, Abdelrazek and Eldeib (2021) conducted a performance evaluation study where he compared the performance of four machine learning algorithms (Logistic Regression, Decision Tree, Random Forest, and SVM) for predicting cervical cancer using data from the NICPR. The Random Forest algorithm had the highest accuracy.

Wang *et al.* (2021) presented a study on predicting cervical cancer using machine learning techniques. A dataset of cervical cancer patients and non-cancerous controls was used to develop a model that could predict whether a patient had cervical cancer or not. They used several feature selection techniques, including the mRMR and CFS algorithms, to identify the most important features for predicting cervical cancer. These techniques helped to reduce the number of features needed for accurate prediction and improved the accuracy of the prediction. Their approach achieved a high accuracy rate for predicting cervical cancer using the random forest algorithm and improved feature selection technique. Bhatti, Shahzad and Asif (2021) conducted a similar study to evaluate the performance of the random forest algorithm in predicting cervical cancer using clinical and demographic data. The authors collected data from 858 patients and divided it into training (70%) and testing sets (30%). They applied the random forest algorithm to the data and evaluated its performance using various metrics. The results showed that the algorithm achieved high accuracy, sensitivity, specificity, positive and negative predictive values, and area under the receiver operating characteristic curve. The study concluded that the random forest algorithm could be a useful tool in predicting cervical cancer, but further research is needed to validate these findings with additional biomarkers and in larger datasets.

Hussein, Mohamed and Aziz (2021) conducted a predictive study for detection of cervical cancer, using Random Forest as the machine learning algorithms. Attributes related to demographic and clinical risk factors were considered as the input phenotypes for the system. The model was trained on data from 1,255 women in Egypt, including age, education, marital status, family history, smoking status, and history of sexually transmitted infections. The evaluated system shows that the Random Forest gave a good prediction performance. Reviewing all the reported studies, it would be observed that none of the studies was said to have used Convolutional Neural Networks, as majority of the studies employed traditional machine learning algorithm. Additionally, most of the used dataset were structured dataset. This is the reason this study developed a system that employed deep learning algorithm with a medical image dataset. This will help in proving a broader scope for the state of art of the study and give an insight of what the performance could be when such technique is employed.

## MATERIALS AND METHOD

The Cervical cancer detection procedure typically consists of four main stages: data acquisition, data pre-processing and image processing, feature extraction and dimensionality reduction, model training and evaluation. Data acquisition is concerned with the collection of isolated cervical Pap smear slides. Pre-processing aims to reduce picture interference and standardise image size and form to ensure consistent dimensions. This is critical for improving detection accuracy. During the feature extraction step, important features from the cervical cancer pictures are extracted. The dimensionality reduction procedure is employed after the feature extraction step to improve classification accuracy. The algorithm is trained and evaluated by feeding it labelled vector data that has been flattened. The evaluation phase focuses on determining how well the model works when supplied with previously unknown data. Figure 3.1 below illustrates a block diagram outlining the stages involved in the cervical cancer detection system. These stages include data acquisition, data preprocessing and image processing feature extraction and dimensionality reduction as model training and evaluation

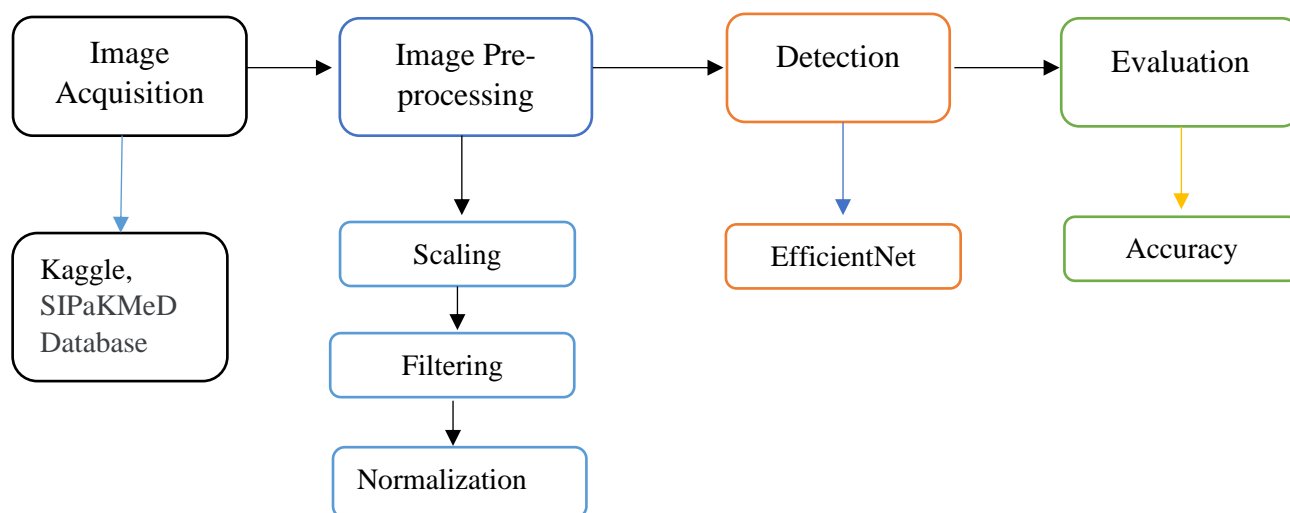


Figure 1: Overview of the research methodology

### Data Acquisition

The dataset used was obtained from Kaggle. SIPaKMeD Database comprises 4049 images of cells that have been manually extracted from 966 groupings of cells, in Pap smear slides. These images were captured using a CCD camera attached to a microscope. The cell images are classified into five categories; superficial intermediate cells, parabasal cells, metaplastic cells, dyskeratotic cells, and koilocytotic cells including normal, abnormal and benign cells. Table 1 provides detailed information of the SIPaKMeD dataset. Table 1 shows the distribution of this dataset based on the type of cells captured in it. As classified in Table 1, superficial-Intermediate cells and parabasal cells are normal cells, metaplastic cells are benign cells while dyskeratotic cells and koilocytotic cells are abnormal cells.

Table 1: Class distribution of different cells in the dataset

Class	Number of Images	Number of Cells
	<b>Normal cells</b>	
Superficial-Intermediate cells	126	831
Parabasal cells	108	787
	<b>Benign Cells</b>	
Metaplastic cells	271	793
	<b>Abnormal Cells</b>	
Dyskeratotic cells	223	813
Koilocytotic cells	238	825
Total	966	4049

### Image Pre-processing

The dataset was taken through series of image pre-processing techniques in order to ensure it was in the right format for processing. The images were firstly resized so that they fell in the same input size as the model, afterwards, they were filtered using low and high pass filtering. This was done to remove noise that might lead to distortion of the image. The 'labels' and 'imgdata' lists were converted into NumPy arrays. Data normalization was then performed using Min-Max normalization technique.

### Detection using EfficientNet

This study employed transfer learning technique, using trained EfficientNet model for classification of the cervical cancer images. The pre-trained EfficientNet model was fine-tuned with parameters and features including architecture, optimization, loss function, and batch size, number of epochs, image dimensions, and filters. The sequential model design seamlessly integrates layers for feature extraction, combining convolutions with ReLU activation, max-pooling, and fully connected components (Khalil *et al.*, 2022). Fine-tuning employed Adam optimizer with a specific learning rate of 0.001, and the sparse categorical cross-entropy loss function was employed for accurate alignment between predictions and true labels. Training efficiently occurred in batches of 32 images over 200 epochs, achieving a balance between computational efficiency and accuracy refinement. Images were resized to a manageable 32 x 32 pixels, finding a pragmatic equilibrium between data quality and processing demands. The strategic integration of diverse filter sizes in convolutional layers enhances the model's capacity to detect features of different scales.

### Evaluation method and Metrics

The system was evaluated using hold-out evaluation method with 60% of the whole dataset assigned for the training, 20% for validation and the remaining dataset was used for testing. After the model was well trained and tested, it was then evaluated using accuracy, precision, f1score and recall. These evaluation metrics results would be gotten through the printed classification report after the model have been tested with the test data split. The mathematical formulation of some of these metrics are represented with Equation 1, 2 and 3.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

## RESULTS AND DISCUSSION

The developed cervical cancer detection system was developed using EfficientNetB7 as the detection model. As mentioned in the earlier section. The system was trained with batch size of 32 over 200 epochs.

Figure 2 shows the training and validation accuracies plotted against Epoch as the model was trained over 200 epochs. As seen in the graph, the training accuracy is more than the validation accuracy with small difference. This shows that our model was well trained and there was nothing like overfitting of model. This helped in having a good performance of the system when evaluated. Though the validation accuracy started way too higher than the starting value of the training accuracy and this made us to know that the training actually considered the accuracy of the system from the possible values without overlooking the smaller ones.

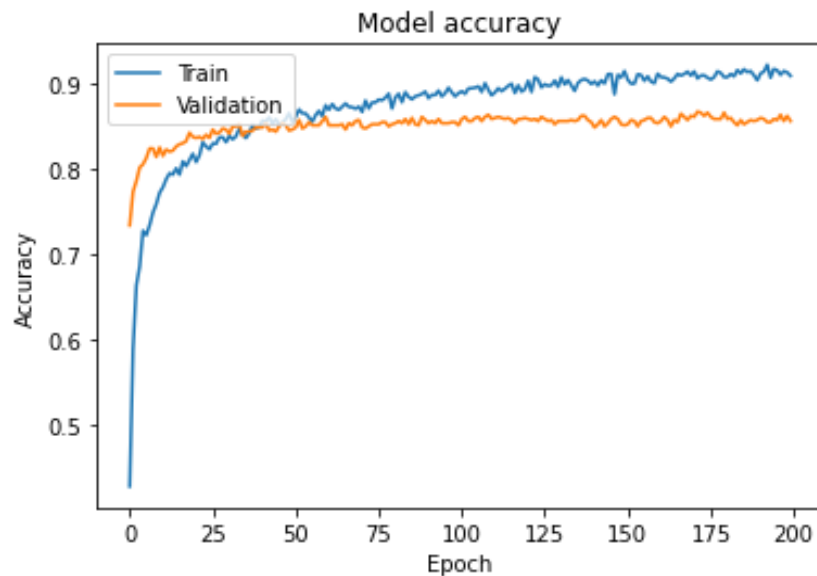


Figure 2: Training and Validation Accuracies per Epoch

Figure 3 shows the training and validation losses plotted against Epoch as the model was trained over 200 epochs. It can be seen in the graph that the training loss is below the validation accuracy with small difference that is less than 20%. This shows that our model was well trained and there was nothing like underfitting of model. This helped in having a good performance of the system when evaluated.

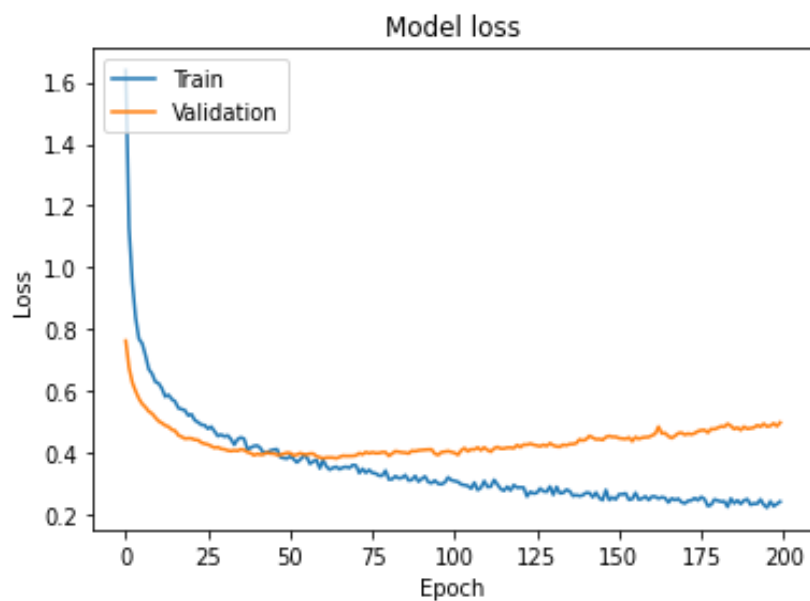


Figure 3: Training and Validation losses per Epoch

As earlier mentioned the system was evaluated using some evaluation metric. This system gave an average accuracy, precision, and F1score of 87, 87 and 87% respectively. Dyskeratotic

cells class gave the highest precision of 98% and F1score of 92%. The summary of these results is presented in Table 2 which shows the classification report gotten during system evaluation.

**Table 2: Classification Report of the Developed System**

Class	Precision	Recall	F1-score	Support
0	0.78	0.86	0.82	160
1	0.85	0.88	0.86	161
2	0.90	0.95	0.92	170
3	0.98	0.89	0.93	152
4	0.85	0.77	0.81	167
Accuracy			0.87	810
macro average	0.87	0.87	0.87	810
Weighted average	0.87	0.87	0.87	810

### Comparison with Machine Learning Algorithms

The performance of the developed system trained with EfficientNetB7 was compared with the performance of Graph Neural Network and Random Forest, so as to showcase the effectiveness of the developed system. When compared, the developed system outperformed the other two machine learning algorithms trained with the same dataset. Table 3 shows the comparison results of the compared algorithms.

**Table 3: Experimental results of the Comparison with some Machine Learning Algorithms**

S/N	Algorithm	Accuracy (%)	F1score (%)
1	Developed system (EfficientNet B7)	87	87
2	Graph Neural Network	51	51
3	Random Forest	83	83

As shown in Table 3, the developed system is 4% more accurate than random forest and 36% more accurate than the graph neural network. The 87% accuracy gotten from the developed system signifies that EfficientNet B7 performed well when used for detection of cervical cancer with medical image dataset.

### CONCLUSION AND RECOMMENDATIONS

This system was developed by employing the flexibility of transfer learning where EfficientNet B7 was used for the detection of cervical cancer using the SIPaKMeD Database that comprises of 4049 images of cells that have been manually extracted from 966 groupings of cells, in Pap smear slides. The developed system gave an average performance accuracy of 87%, and when compared with some machine learning algorithms like Graph Neural Network and Random Forest, the two were outperformed by the developed system. This obviously expresses the efficiency of EfficientNet B7 for the detection of cervical cancer using medical images. Other architectures of CNN like ResNet, Visual Geometry Group (VGG), AlexNet and others should be implemented in the future works to check their performance with the developed system and a larger dataset might be utilized for deep learning of the model.

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