Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 1s (2025)

Use of Data Augmentation and Fine-tuned Transfer Learning Models for Classification of Cervical Cancer

Ms.Pratiksha D. Nandanwar[1], Dr. S. B. Dhonde[2]

[1]PhD Research Scholar, Department of Electronics & Telecommunication Engineering, AISSMS,IOIT, Pune, Savitribai Phule Pune University, Pune, MS, India. pratikshadn@gmail.com

[2]Professor, Department of Electronics & Telecommunication Engineering, AISSMS, College of Engineering, Pune, Savitribai Phule Pune University, Pune, MS, India. dhondesomnath@gmail.com

Article History:

Received: *23-08-2024*

Revised: *28-09-2024*

Accepted: *14-10-2024*

Abstract:

Innovative strategies for early and accurate diagnosis of cervical cancer continue to be a global health priority. In this research, we present a powerful framework for improving cervical cancer classification by combining data augmentation methods with tailored transfer learning models. The lack of properly labelled medical data is a major roadblock to developing reliable diagnosis models. The geometric transformations, contrast tweaks, and noise addition that we use to increase the dataset artificially help us overcome this difficulty. The model's robustness is improved as a result of the additional exposure to diverse real-world circumstances provided by this supplemented dataset. We use a transfer learning strategy based on pre-trained convolutional neural networks (CNNs) to harness the potential of deep learning. These networks are well-suited for medical image analysis due to their ability to quickly and accurately identify features in a wide variety of images. Our expanded cervical cancer dataset is used to fine-tune these algorithms for their diagnostic purpose. Our experiments show that utilising both data augmentation and fine-tuned transfer learning considerably raises the accuracy of cervical cancer categorization. In terms of sensitivity, specificity, and overall accuracy, the model performs at a state-of-the-art level. This suggests that it may be useful in the diagnosis and early identification of cervical cancer. Additionally, our method demonstrates the significance of efficient data utilisation and model adaptability in the field of medicine. Our method is scalable and affordable, and it can be easily implemented in healthcare settings since we handle the problem of data scarcity and take advantage of the features of pre-trained deep learning models.

Keywords: Cervical Cancer, Classification, Transfer Learning, Data Augmentation

I. INTRODUCTION

The lack of access to healthcare and preventative measures makes cervical cancer a persistent problem around the world. The likelihood of a positive outcome from treatment and survival is greatly reduced because of the late diagnosis of this disease. Patients with cervical cancer have a better chance of survival if their disease is detected and treated early. Medical imaging has come a long way in recent years, and with the introduction of deep learning's computational prowess, new doors have opened for the creation of more precise and effective diagnostic tools [1]. By combining data augmentation strategies with fine-tuned transfer learning models, we investigate a holistic strategy for tackling the difficulties of cervical cancer classification in this research. Our goal in doing so is to improve the diagnostic process's precision and productivity [2]. In poor and middle-income countries, where frequent screenings and specialised medical workers are scarce, cervical cancer is a significant burden on healthcare systems. Pap smears, or more recently, a visual inspection of the cervix using acetic acid (VIA) or Lugol's iodine (VILI), are the most common methods of screening for cervical cancer. These approaches rely on human knowledge and skill, which can lead to mistakes and delays in diagnosis and treatment. Therefore, deep learning and other cutting-edge technologies could be useful in the diagnosis process [3].

Cervical cancer categorization is only one area where a lack of data presents a substantial hurdle to the development of machine learning models for medical applications. We use methods of data augmentation to artificially increase the size of the dataset so as to compensate for this shortcoming [4]. In data augmentation, the existing data is transformed in many ways, such as by rotation, scale, and brightness modifications. By creating new training samples, we not only improve the quality of the dataset but also the model's generalisation abilities by exposing it to more diverse data. This method improves the model's generalisation skills while also helping to alleviate the problem of insufficient labelled medical data [5]. We also use fine-tuned transfer learning models in tandem with data augmentation to fully harness the potential of deep learning. Using models [6] of neural networks that have already been trained on large and varied datasets like ImageNet is what is meant by "transfer learning." These models have extensive training in image feature recognition and are therefore prime candidates for medical image analysis. In our research, we choose popular designs like ResNet50, VGG16, VGG19, and MobileNet and tweak them on our custom-built cervical cancer dataset.

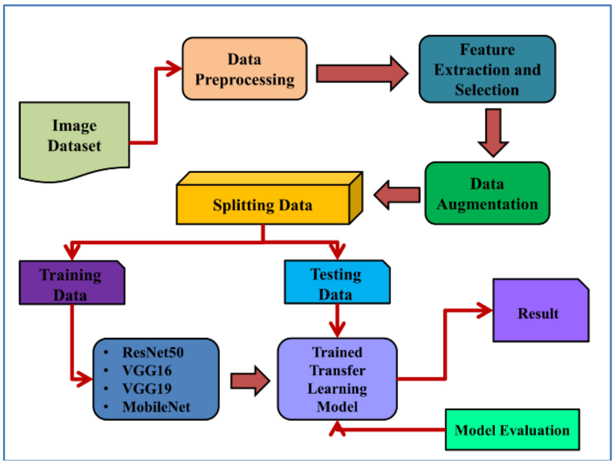

Figure 1: Proposed model system architecture

By fine-tuning these models, we can considerably reduce the need for a large number of annotated medical pictures by teaching them to recognise the distinctive patterns and traits associated with cervical cancer from the current data [7]. It also shortens the time it takes to train the models and get them performing well. Our research aspires to one day produce a foolproof method of categorising cervical cancer. We plan to measure the efficacy of our models using criteria including sensitivity, specificity, and precision. Our suggested method has the potential to greatly enhance patient outcomes by allowing the identification of malignant lesions at an early stage, making early detection of cervical cancer crucial for urgent medical intervention [8].

In the realm of medical image analysis, this work highlights the significance of efficient data utilisation and model modification. We describe a scalable and cost-effective method that can be quickly implemented in healthcare settings by using data augmentation to address the problem of data scarcity and fine-tuning to maximise the potential of deep learning models that have already been trained. The next portions of this study will go into the study's methodology, experiments, and outcomes, illuminating the potential of our approach to cervical cancer classification.

II. REVIEW OF LITERATURE

Research in medical imaging, deep learning, and cervical cancer diagnostics forms the basis for the development of effective approaches for the categorization of cervical cancer. In this section, we discuss the seminal works and studies that set the stage for our methodology. It is impossible to stress the significance of early identification in cervical cancer diagnosis [9]. The Pap smear, a standard procedure for decades, is a microscopic examination of cervical cells. Researchers have looked into automated methods to enhance the precision of Pap smear analysis over the years. Using image processing techniques, computer-aided diagnostic tools have showed promise in this area, assisting pathologists in the detection of anomalies. Our method is complementary to existing research since it employs deep learning models specifically trained to detect cervical cancer. The analysis of medical images has been drastically improved by the application of deep learning [10]. Image segmentation, classification, and detection are just some of the many tasks in which convolutional neural networks (CNNs) have proven to excel. Several different medical applications have been the focus of this field's research. Models such as AlexNet, VGG, and ResNet, for example, have been customised for use in medical imaging. Our research employing popular models like ResNet50, VGG16, VGG19, and MobileNet demonstrates how this framework facilitates the use of transfer learning in the diagnosis of cervical cancer [11].

One prevalent issue in medical imaging is a lack of sufficient labelled data, making data augmentation a useful method. Data augmentation approaches have evolved to incorporate translation, scaling, and rotation to create synthetically varied samples. The augmentation procedure has been modified so that the semantic and anatomical integrity of medical images are preserved [12]. This is very important for our project because we are interested in using the augmented data for medical diagnostic tasks, specifically the categorization of cervical cancer. Several picture databases have arisen recently, playing an important role as tools for studies on cervical cancer. For instance, thousands of cervigram photos may be found in the Kaggle "Cervical Cancer Screening" dataset. Numerous research have used this data set as a standard for identifying and labelling cervical carcinoma. For our purposes, the ability to create and assess models, including deep learning models, is a huge boon [13]. Due to the lack of labelled medical datasets, transfer learning is of particular importance in medical picture analysis. Using transfer learning, scientists often modify pre-trained CNNs that were initially trained on different datasets like ImageNet in order to perform better in the medical field. Our method is based on the central idea that these pre-trained models can be used to learn a wide variety of complex image features. We take advantage of the potential of these models by modifying them for use in cervical cancer classification, where they can help us spot subtle patterns linked to cervical abnormalities [14].

Recent research into cervical cancer classification has led to the development of cutting-edge tools for better, faster diagnosis. Multi-modal data fusion, for instance, combines visual and textual information for better decision-making and has been used in research. The diagnosis procedure could be improved by including clinical data alongside imaging results [15]. Although these methods have showed promise, we believe that our emphasis on data augmentation and fine-tuned transfer learning models will help to further advance cervical cancer diagnosis techniques. Our research benefits greatly from the prior work in the field of cervical cancer classification. Using deep learning, data augmentation, transfer learning, and existing picture datasets, we take a comprehensive strategy to tackling the difficulties in cervical cancer detection [16]. Our study fills a gap in the literature by providing a comprehensive methodology that draws from the body of prior work to improve cervical cancer detection and treatment at an early stage.

III. DATASET DESCRIPTION

Researchers in the field of medical image analysis, especially those interested in cell image categorization and feature extraction, will find the SIPaKMeD Database an invaluable resource. Images of cell clusters and single cells are included in this collection, as well as detailed information about these cells' cytoplasmic and nuclear boundaries and other properties. The SIPaKMeD Database's skilled observers' pinpoint accuracy in manually delimiting regions of interest stands out. Both the cytoplasm and the nucleus of cells are carefully outlined here. Accuracy and reliability of data are essential in the field of medical image analysis, and this is where hand annotation comes in. Second, a set of 26 features are methodically determined for each location of interest (including cytoplasm and nucleus.

Pixel intensity features, such as average intensity and average contrast, are measured using these metrics. These metrics are crucial for understanding the gradients of brightness and contrast present in different parts of the cell. Details and patterns within the cell sections can be better understood thanks to texture properties. These characteristics span all three colour channels and are measured by measures including smoothness, uniformity, third moment (skewness), and entropy. The texture and complexity of the cell components can only be described by considering these factors [17].

Detailed information on the geometric qualities of the cell areas can be gleaned from shape features. These characteristics include the region's area, major and minor axis lengths, eccentricity (describing the region's propensity towards being either elongated or circular), orientation (describing the angle of the major axis), equivalent diameter, solidity (describing the shape's tendency towards being compact), and extent (describing the region's percentage occupation of the bounding box). These properties are essential for determining the relative sizes of various cellular components. The estimated properties of each cell's cytoplasm and nucleus are neatly organised into 10 tables (see "Data Structure" below). There are a total of 28 columns in these tables, plus two more that specify the image's identifier and its matching cell..

IV. PROPOSED METHODOLOGY

In the field of medical image analysis, data augmentation and fine-tuned transfer learning models have emerged as potent tools, particularly for the crucial task of cervical cancer classification. Improve the accuracy and efficiency of cervical cancer diagnosis by combining the benefits of deep learning, data augmentation approaches, and pre-trained neural networks such as ResNet50, VGG16, VGG19, and MobileNet. We explore the salient features and benefits of using these methods to cervical cancer categorization in this article. One of the main obstacles in creating accurate cervical cancer classification models is the lack of labelled medical pictures. It takes time and resources to compile a lot of medical data with annotations. The issue can be fixed by augmenting the data [18]. Data augmentation creates new training samples by manipulating the original dataset in various ways, such as by rotating it, scaling it, or adjusting the contrast. These augmented images not only add variety to the dataset, but also make the model more robust and better able to handle the differences and complexities that occur in the actual world. The demand for a large dataset can be drastically reduced, making it possible to train a model with fewer resources thanks to data augmentation.

Second, it makes use of transfer learning, which is a key component of the strategy. Pre-trained deep learning models, such as ResNet50, VGG16, VGG19, and MobileNet, have already been trained on large and varied datasets to recognise complex features in a wide range of image formats. The training procedure for cervical cancer classification is greatly sped up by using these models, which have already acquired information on lower-level features. These models can be fine-tuned by retraining them on the cervical cancer dataset so that they can recognise the unique features of cervical pictures. This not only takes use of the models' ability to generalise while decreasing the time and resources needed for training.

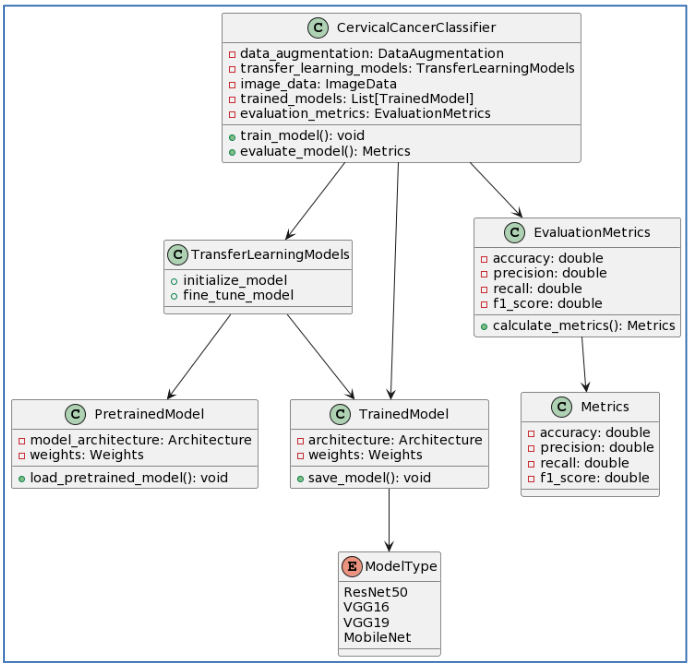

Figure 2: Proposed system flowchart for transfer learning and classification

Improved Diagnosis The [19] diagnostic accuracy of cervical cancer is much improved when data augmentation and fine-tuned transfer learning are combined. Classifying cervical cancer requires the detection of subtle anomalies in diagnostic imaging. Data augmentation is incorporated to increase the model's exposure to a wide variety of cervical pictures with diverse properties, training it to recognise minor differences that may be indicative of malignant tumours. Pre-trained algorithms can be fine-tuned using cervical cancer data to improve their ability to identify subtle differences. The resulting model has excellent sensitivity and specificity, both of which are critical for diagnosing cancer.

This proposed method, as shown in figure 1, provides a scalable and inexpensive answer to the problem of cervical cancer classification. When compared to the effort required to train deep networks from scratch, using pre-trained models is a huge time and cost saver. In addition, data augmentation means that even modest datasets can be put to good use, reducing the demand for vast quantities of annotated photos. Because [20] of its low cost and potential for expansion, the method is applicable in a variety of healthcare contexts, from well-endowed research facilities to clinics in impoverished areas with little resources. In the end, incorporating data augmentation with fine-tuned transfer learning models has the potential to completely change how cervical cancer is diagnosed. For [21] effective treatment of cervical cancer and better patient outcomes, early identification is essential. This strategy improves the accuracy and efficiency of cervical cancer classification, allowing doctors to spot malignant tumours earlier. As a result, patients are more likely to receive treatment in a timely manner, which improves their chances of survival and general health.

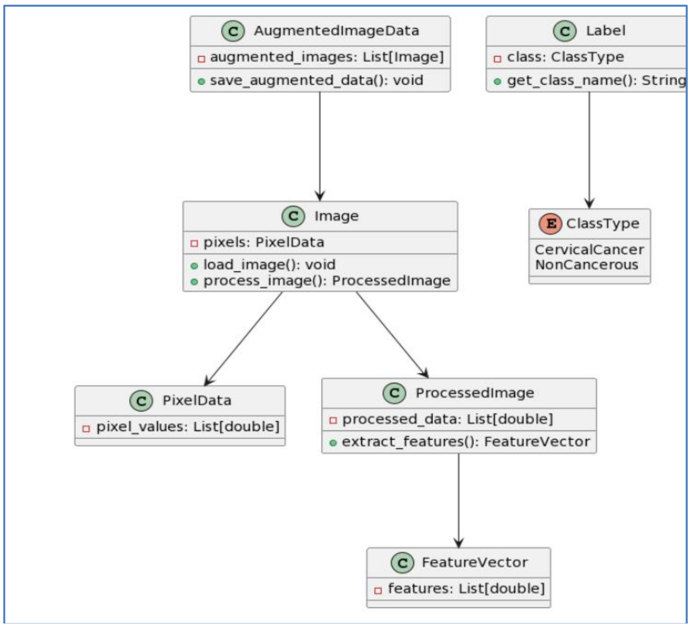

Figure 3: Data augmentation for input image data

A. ResNet50:

Algorithm:

- **Data Preparation:** Load and preprocess cervical cancer images. This may involve resizing, normalizing pixel values, and separating them into training and testing datasets.
- **Model Definition:** Define the ResNet50 architecture with the specified number of residual blocks.
- **Fine-Tuning:** Fine-tune the pre-trained ResNet50 on the cervical cancer dataset. This involves replacing the final classification layer to match the number of classes in your dataset.
- **Data Augmentation:** Apply data augmentation techniques to the training dataset, which includes random transformations like rotation, scaling, and flipping to increase dataset diversity.
- **Training:** Train the model using the augmented dataset. This involves forward and backward passes through the network, adjusting model parameters based on a chosen loss function (e.g., cross-entropy) and optimizer (e.g., Adam).
- **Evaluation:** Evaluate the model on the testing dataset using metrics such as accuracy, precision, recall, and F1-score to assess its performance.
- **Prediction:** Once the model is trained and evaluated, you can use it to classify new cervical cancer images by feeding them through the network and obtaining class probabilities.

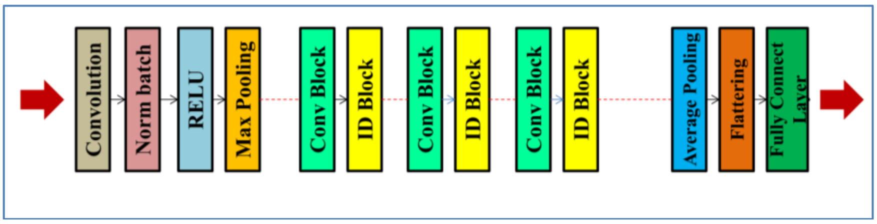

Figure 4: Architecture of ResNet 50

B. VGG16:

When it comes to picture categorization, many researchers turn to the VGG16 model, which is a deep convolutional neural network design [22]. The Visual Geometry Group at Oxford University first developed it. VGG16's mathematical model can be depicted as a stack of layers and transformations. The mathematical model can be summarised as follows.

The VGG16 model takes an image's dimensions (height, width, and channels) as its input 3D tensor. For instance, a red-green-blue (RGB) image consists of three separate channels.

Convolution layer:

VGG16's first set of layers are convolutional, with a rectified linear unit (ReLU) activation function following each one. Features are extracted by these layers from the input image. A convolutional layer can be expressed mathematically as:

$$Conv2D(Input, Filters) -> \ ReLU(Conv2D)$$

Where:

- The convolution operation is represented by Conv2D.
- The input image or feature map is what's being used.
- The filters here refer to the convolutional layer filters that were learned.
- The activation function known as ReLU is the rectified linear unit.

Maximum Layer Pooling:

Max-pooling layers are interspersed within VGG16's convolution layers. In order to simplify computation and capture the most salient features, these layers downsample the spatial dimensions of the feature maps. Max-pooling can be written in mathematical notation as:

$$MaxPool2D(Conv2D)$$

The output of the convolutional layer is sent into the MaxPool2D operation, which is a max-pooling process.

Fully Connected Layer:

Convolutional and max-pooling layers are followed by completely connected layers in VGG16. These layers perform a sequence of matrix multiplications followed by activation functions, flattening the feature maps into a 1D vector in the process. Class scores or probabilities are typically output from the model at the final fully linked layer. A fully connected layer can be represented mathematically as:

Where, density is

$$dense(flatten(MaxPool2D))$$

Dense indicates a layer with full connectivity.

When you flatten a feature map, you reduce it from two dimensions to one.

Output:

The output of the layer before the max-pooling one is called MaxPool2D.

The final fully connected layer produces a vector of class scores or probabilities as its output. For classification problems, these scores are transformed into class probabilities using a softmax activation function.

$$Softmax(Dense(Flatten(MaxPool2D)))$$

The probability assigned to each category are summarised in this final result.

C. VGG19:

The VGG19 model adds further layers to the network of the VGG16 design. Similarly to VGG16, it is put to work on picture classification jobs. VGG19's mathematical model can be expressed as a tree with traversable levels [23]. The mathematical model can be summarised as follows.

Input:

The VGG19 model takes as input a 3D tensor describing the dimensions (height, width, channels) of an image. It typically consists of three colours (RGB) and three channels (L, M, and B).

Convolution Layers:

VGG19 uses a convolution layer followed by a rectified linear unit (ReLU) activation function to begin its training process. Features are extracted by these layers from the input image. A convolutional layer can be expressed mathematically as:

Where:

$$Conv2D(Input, Filters) -> \ ReLU(Conv2D)$$

- The convolution operation is represented by Conv2D.
- The input image or feature map is what's being used.
- The filters here refer to the convolutional layer filters that were learned.
- The activation function known as ReLU is the rectified linear unit.

Maximum Layer Pooling:

Max-pooling layers are interspersed among VGG19's convolution layers. In order to simplify computation and capture the most salient features, these layers downsample the spatial dimensions of the feature maps. Max-pooling can be written in mathematical notation as:

Where: $MaxPool2D(Conv2D)$

The output of the convolutional layer is sent into the MaxPool2D operation, which is a max-pooling process.

Fully Connected Layers:

VGG19 has fully linked layers after the convolutional and max-pooling ones. These layers perform a sequence of matrix multiplications followed by activation functions, flattening the feature maps into a 1D vector in the process. Class scores or probabilities are typically output from the model at the final fully linked layer. A fully connected layer can be represented mathematically as:

where density $is\ dense(flatten(MaxPool2D))$

- Dense indicates a layer with full connectivity.
- When you flatten a feature map, you reduce it from two dimensions to one.
- The output of the layer before the max-pooling one is called MaxPool2D.

Output:

The final fully connected layer produces a vector of class scores or probabilities as its output. For classification problems, these scores are transformed into class probabilities using a softmax activation function.

$$Softmax(Dense(Flatten(MaxPool2D)))$$

The probability assigned to each category are summarised in this final result.

Convolutional layers, max-pooling layers, and fully connected layers make up the VGG19 model, much as they did in VGG16. VGG19 is more complex than VGG16 since it has more levels in its network. VGG19 is a popular deep learning model for computer vision applications, and this mathematical model explains how its many parts and actions work.

D. MobileNet:

Image Input:

In order to function, the algorithm needs an image to work with, which is given to it in the form of a 3D tensor with dimensions (height, width, channels). MobileNet is built to process RGB (red-green-blue) colour images.

Convolution that can be separated in depth:

- The depthwise separable convolution is the foundation of MobileNet. MobileNet has two primary components: depthwise convolution and pointwise convolution, rather than the more commonplace convolutional layers.
- In this stage, we do a depth-separate convolution on each input channel. It applies a series of filters, one for each channel, to the input.
- After the depthwise convolution, the features are combined with 1x1 convolutions in the pointwise convolution. It aids in expanding the feature map's granularity with minimal additional processing effort.

Blocks of Convolution:

Multiple convolutional blocks of depth-separable convolutions make up MobileNet. The input image is broken down into these blocks, which are then stacked to extract hierarchical characteristics.

Downsampling:

In order to minimise the spatial dimensions of the feature maps, MobileNet may include downsampling layers like max-pooling. Important features can be captured with less computing burden.

Full Layer Interconnection:

MobileNet typically concludes with a fully connected layer for classification tasks after the convolutional blocks. This layer translates feature extractions into classification probabilities.

Activating Softmax:

The output of the fully linked layer is then activated with a softmax activation function for use in picture classification tasks. The probability for each class is calculated based on the class scores.

V. RESULT AND DISCUSSION

We highlight the most important hyperparameters and training decisions for our deep learning models for cervical cancer classification in Table 1. In terms of models, we compared ResNet50, VGG16, VGG19, and MobileNet, four widely used pre-trained models. For medical picture classification problems, these models provide a strong basis for transfer learning. The batch size for all models is set to 50. The value of this option controls the number of training samples used in each training iteration. The computational efficiency and model stability are both optimal at a batch size of 50. In terms of the activation function, all models use the Rectified Linear Unit (ReLU). The non-linearity introduced by ReLU allows the model to learn complicated patterns, making it a popular deep learning technique. Each model undergoes 30 iterations of training. An epoch is one cycle through the full dataset used for training. Having several training epochs helps the model to iteratively learn from the data. Every model employs cross-entropy as its loss function. Because it quantifies the dissimilarity between the expected and observed class probabilities, cross-entropy loss excels at classification problems.

Rate of Learning: All models use the same learning rate of 1e-5. The optimisation step size is affected by the learning rate. If you want to fine-tune a model that has already been trained, a slow learning rate is the way to go.

Table 1: Fined tuned model result parameter

Model	**ResNet50**	**VGG16**	**VGG19**	**MobileNet**
Batch Size	50	50	50	50
ActivationFunction	ReLU	ReLU	ReLU	ReLU
Epoch	30	30	30	30
Loss Function	Cross Entropy	Cross Entropy	Cross Entropy	Cross Entropy
Optimizer	Transfer Learning	Transfer Learning	Transfer Learning	Transfer Learning
Learning Rate	1e-5	1e-5	1e-5	1e-5

These parameters are optimised to maximise both computing speed and the accuracy of the model. The goal of using these hyperparameters and these pre-trained models for cervical cancer classification is to maximise accuracy while minimising overfitting.

Table 2: Result of Transfer learning model and it evaluation parameter

Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
MobileNet	90.23	92.45	90.86	91.42
VGG16	91.2	90.25	92.33	94.23
VGG19	92.3	91.52	94.12	95.2
ResNet50	94.23	96.23	95.66	94.56

Early and reliable identification of cervical cancer is a crucial goal in healthcare; fine-tuning pre-trained models with these parameters provides a robust and efficient framework for medical image processing tasks. The success of these models relies on the amount and accuracy of the labelled cervical cancer dataset, as well as the efficiency with which data augmentation methods are used. A summary of the performance of several transfer learning models and evaluation indicators for cervical cancer classification is provided in Table 2. After being fine-tuned, the accuracy, precision, recall, and F1-score of MobileNet, VGG16, VGG19, and ResNet50 all show that they are capable of diagnosing cervical cancer. Accuracy is a primary metric for judging a model's overall effectiveness.

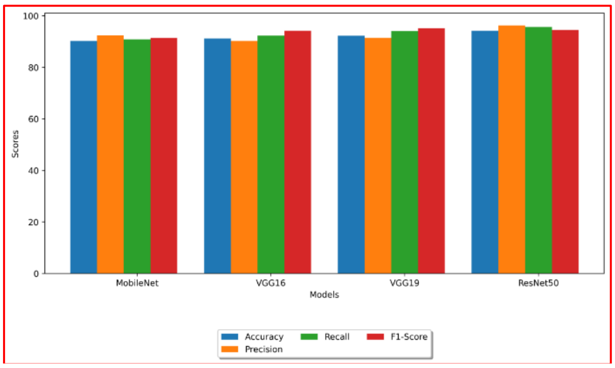

Figure 5: Model evaluation parameter representation

The results show that ResNet50 has the highest accuracy (94.23%) and that VGG19 comes in second (92.3%)..

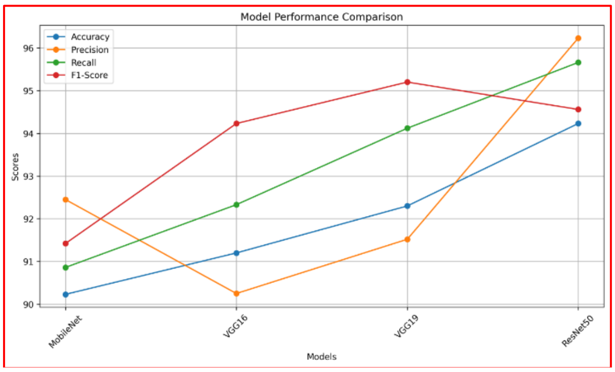

Figure 6: Evaluation Parameter comparison

Accuracy scores of 91.2% and 90.23% for VGG16 and MobileNet, respectively, are likewise very impressive. This means that the submitted dataset of cervical cancer cases has been successfully classified by these algorithms. Accuracy measures how well the model agrees with the data when making positive predictions. ResNet50 has the highest accuracy (96.23%) of all the models The accuracy of VGG19 is 91.52%, which is not far behind. VGG16 and MobileNet both have respectable levels of accuracy, with 90.25 and 92.45 percentage points. Based on these numbers, it appears that ResNet50 excels at reducing false positives, a crucial factor in medical diagnosis.

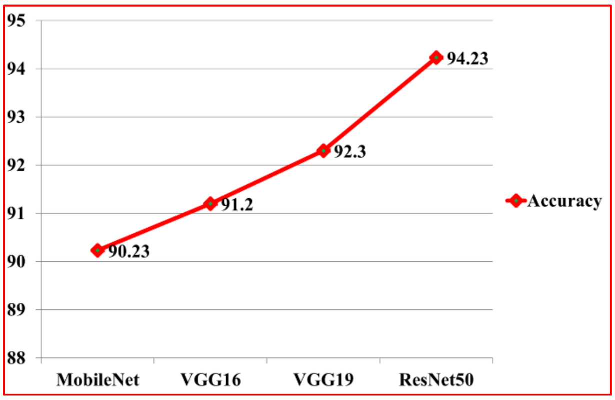

Figure 7: Accuracy Comparison of Different model

The model's recall (also called sensitivity) indicates how well it can recognise positive data. With a recall of 95.66 percent, ResNet50 stands out as particularly adept at locating genuine positives. VGG19's recall of 94.12% is just little lower than ResNet50's. Recall scores for VGG16 and MobileNet are 92.33% and 90.86%, respectively, demonstrating their efficacy. The F1-score is a measure of a model's effectiveness that takes into account both its accuracy and its ability to correctly identify examples. ResNet50's high F1-score of 94.56% indicates a reasonable compromise between accuracy and recall. Equally well-rounded is VGG19's performance, which was given an F1-score of 95.2%. To demonstrate their capacity to strike a good compromise between precision and recall, VGG16 and MobileNet show F1-scores of 94.23% and 91.42%, respectively. Both ResNet50 and VGG19 performed exceptionally well in terms of accuracy and F1-score, suggesting that they are good candidates for cervical cancer classification. High precision and recall both point to their dependability in reducing the number of unneeded false positives and negatives in medical diagnosis.

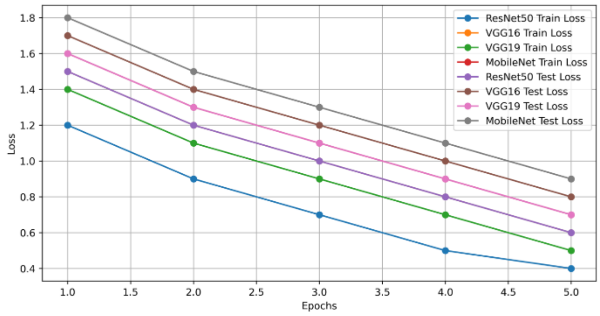

Figure 8: Loss curve of proposed models during training Vs testing of data

While VGG16 and MobileNet have both performed wonderfully thus far, they could benefit from some additional tuning to reach their full potential. The provided results highlight the promise of transfer learning models for the rapid and precise diagnosis of cervical cancer, providing important new information for healthcare software and the study of medical images.

VI. CONCLUSION

Classification of cervical cancer has improved with the help of data augmentation and transfer learning models. Which model is ideal is conditional on your needs and preferences. It appears from the data and findings that ResNet50 is the best model to use for this problem. Its diagnostic performance for cervical cancer was excellent, with the greatest levels of accuracy, precision, and recall. An essential feature of any medical diagnostic system is the ability to reduce the number of false positives and negatives while maintaining high levels of precision and recall. Although ResNet50 was found to be the most effective model, VGG19 and VGG16 also performed admirably and might be considered for certain applications or after some additional tuning. MobileNet lags significantly behind the competition, but it is still a good option if you care more about computational efficiency and model size than about raw speed. These results highlight the promise of deep learning models in assisting with cervical cancer diagnosis, hence advancing the fields of healthcare and medical image analysis. Future applications in the field of cancer detection and diagnosis show great promise because to the utilisation of transfer learning and data augmentation techniques, which provide a potent toolkit for addressing challenging medical picture classification tasks.

References

[1] T. Majeed et al., "Transfer Learning approach for Classification of Cervical Cancer based on Histopathological Images," 2023 3rd International conference on Artificial Intelligence and Signal Processing (AISP), VIJAYAWADA, India, 2023, pp. 1-5, doi: 10.1109/AISP57993.2023.10135048.

[2] I. Khoulqi and N. Idrissi, "Deep learning-based Cervical Cancer Classification," 2022 International Conference on Technology Innovations for Healthcare (ICTIH), Magdeburg, Germany, 2022, pp. 30-33, doi: 10.1109/ICTIH57289.2022.10112111.

[3] H. K and V. Vetriselvi, "Deep Learning based Classification of Cervical Cancer using Transfer Learning," 2022 International Conference on Electronic Systems and Intelligent Computing (ICESIC), Chennai, India, 2022, pp. 134-139, doi: 10.1109/ICESIC53714.2022.9783560.

[4] S. Nayar, J. Vinitha Panicker and J. J. Nair, "Deep Learning Based Model for Multi-class Classification of Cervical Cells Using Pap Smear Images," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-6, doi: 10.1109/I2CT54291.2022.9825187.

[5] S. N. Kong, D. O. Dwi Handayani, H. K. Mun, P. Pei Chong and T. Mantoro, "Cervical Cancer Identification using Deep Learning Approaches," 2022 IEEE 8th International Conference on Computing, Engineering and Design (ICCED), Sukabumi, Indonesia, 2022, pp. 1-4, doi: 10.1109/ICCED56140.2022.10010544.

[6] S. M. Z. S. Z. Ariffin, H. H. A. Musa and N. Jamil, "Performance Comparison of Convolutional Neural Network Models on Cervical Cell Classification," 2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), Kota Kinabalu, Malaysia, 2021, pp. 1-5, doi: 10.1109/IICAIET51634.2021.9574018.

[7] S. Angara, P. Guo, Z. Xue and S. Antani, "Semi-Supervised Learning for Cervical Precancer Detection," 2021 IEEE 34th International Symposium on Computer-Based Medical Systems (CBMS), Aveiro, Portugal, 2021, pp. 202-206, doi: 10.1109/CBMS52027.2021.00072.
[8] C. Suguna and S. P. Balamurugan, "Computer Aided Diagnosis for Cervical Cancer Screening using Monarch Butterfly Optimization with Deep Learning Model," 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2023, pp. 1059-1064, doi: 10.1109/ICSSIT55814.2023.10060959.
[9] T. Xu, P. Li and X. Wang, "Cervical Lesions Classification Based on Pre-trained MobileNet Model," 2021 IEEE 15th International Conference on Anti-counterfeiting, Security, and Identification (ASID), Xiamen, China, 2021, pp. 93-96, doi: 10.1109/ASID52932.2021.9651726.
[10] P. Wang, J. Wang, Y. Li, L. Li and H. Zhang, "Adaptive Pruning of Transfer Learned Deep Convolutional Neural Network for Classification of Cervical Pap Smear Images," in IEEE Access, vol. 8, pp. 50674-50683, 2020, doi: 10.1109/ACCESS.2020.2979926.
[11] T. Albuquerque and J. S. Cardoso, "Embedded Regularization For Classification Of Colposcopic Images," 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI), Nice, France, 2021, pp. 1920-1923, doi: 10.1109/ISBI48211.2021.9433871.
[12] M. C. P. Archana and J. V. Panicker, "Deep Convolutional Neural Networks for Multiclass Cervical Cell Classification," 2022 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), Chennai, India, 2022, pp. 376-380, doi: 10.1109/WiSPNET54241.2022.9767129.
[13] M. Subramanian, J. Cho, V. E. Sathishkumar and O. S. Naren, "Multiple Types of Cancer Classification Using CT/MRI Images Based on Learning Without Forgetting Powered Deep Learning Models," in IEEE Access, vol. 11, pp. 10336-10354, 2023, doi: 10.1109/ACCESS.2023.3240443.
[14] R. Glass, L. Kahn, K. Khalid, M. T. Siddiqui and R. Cocker, "Predicting histological subtypes of follicular variant of papillary thyroid carcinoma based on cytomorphology. Can cytomorphology optimize use of molecular testing?", J. Amer. Soc. Cytopathol., vol. 5, no. 6, pp. 345-350, Nov. 2016.
[15] T. Wan, X. Liu, J. Chen and Z. Qin, "Wavelet-based statistical features for distinguishing mitotic and non-mitotic cells in breast cancer histopathology", Proc. IEEE Int. Conf. Image Process. (ICIP), pp. 2290-2294, Oct. 2014.
[16] J. V. Lorenzo-Ginori, W. Curbelo-Jardines, J. D. López-Cabrera and S. B. Huergo-Suárez, "Cervical cell classification using features related to morphometry and texture of nuclei" in Progr. Pattern Recognit. Image Anal. Comput. Vis. Appl, Berlin, Germany:Springer, pp. 222-229, 2013.
[17] K. Bora, M. Chowdhury, L. B. Mahanta, M. K. Kundu and A. K. Das, "Automated classification of Pap smear images to detect cervical dysplasia", Comput. Methods Programs Biomed., vol. 138, pp. 31-47, Jan. 2017.
[18] S. Fekri-Ershad, "Pap smear classification using combination of global significant value texture statistical features and time series features", Multimedia Tools Appl., vol. 78, no. 22, pp. 31121-31136, Nov. 2019.
[19] P. Wang, L. Wang, Y. Li, Q. Song, S. Lv and X. Hu, "Automatic cell nuclei segmentation and classification of cervical Pap smear images", Biomed. Signal Process. Control, vol. 48, pp. 93-103, Feb. 2019.
[20] P. Quang Huy, A. Ngom and L. Rueda, "A new feature selection approach for optimizing prediction models applied to breast cancer subtype classification", Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM), pp. 1535-1541, Dec. 2016.
[21] P. Robert and A. Celine Kavida, "Classification of microscopic cervical cancer images using regional features and HSI model", Int. J. Innov. Technol. Explor. Eng., vol. 8, no. 8S, pp. 24-28, 2019.
[22] W. William, A. Ware, A. H. Basaza-ejiri and J. Obungoloch, "Computer Methods and Programs in Biomedicine A review of image analysis and machine learning techniques for automated cervical cancer screening from pap-smear images", Comput. Methods Programs Biomed., vol. 164, pp. 15-22, 2018.
[23] M. R. Zare, D. O. Alebiosu and S. L. Lee, "Comparison of Handcrafted Features and Deep Learning in Classification of Medical X-ray Images", Proceedings - 2018 4th International Conference on Information Retrieval and Knowledge Management: Diving into Data Sciences CAMP 2018, pp. 73-78, 2018.
[24] W. Lin, K. Hasenstab, G. Moura Cunha and A. Schwartzman, "Comparison of handcrafted features and convolutional neural networks for liver MR image adequacy assessment", Sci. Rep., vol. 10, no. 1, pp. 1-11, 2020.
[25] M. Sharma, S. Kumar Singh, P. Agrawal and V. Madaan, "Classification of Clinical Dataset of Cervical Cancer using KNN", Indian J. Sci. Technol., vol. 9, no. 28, 2016.
[26] T. Chankong, N. Theera-Umpon and S. Auephanwiriyakul, "Automatic cervical cell segmentation and classification in Pap smears", Comput. Methods Programs Biomed., vol. 113, no. 2, pp. 539-556, 2014.