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DATA AUGMENTATION AND PRETRAINED TRANSFER LEARNING APPROACHES FOR AUTOMATED CERVICAL CANCER DETECTION

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Abstract

Cervical cancer is still the top cause of death in women around the world, especially in places where early screening and diagnosis services are hard to get to. Thanks to progress in artificial intelligence (AI) and medical images, automatic recognition systems can help doctors make more accurate diagnoses and do less work by hand. This research shows a full system that uses extra data and pre-trained transfer learning models to automatically sort medical images of cervical cancer into different types. To deal with the problems that come with having small and uneven datasets, a full data enhancement process is set up. This adds changes in direction, brightness, and contrast to the datasets to help the models generalise better. A number of cutting-edge convolutional neural networks (CNNs), such as ResNet50, VGG16, VGG19, and MobileNet, are fine-tuned on the new dataset. Performance measures like accuracy, precision, recall, and F1-score are used to judge the models. It was shown in experiments that the fine-tuned ResNet50 model works better than others, with an F1-score of 93.9% and an accuracy of 94.8%. This proves that transfer learning works in the medical imaging area. The suggested method also cuts down on training time by a large amount and improves classification performance while using very few computing resources. This study shows how mixing enhancement with pre-trained models improves stability and scaling. This provides a useful way to help doctors find cervical cancer early and accurately. Multi-modal data fusion and real-time application in healthcare situations will be looked into in more detail in the future.

Keywords: Cervical Cancer Detection, Data Augmentation, Transfer Learning, Pretrained CNN Models, Medical Image Classification, Deep Learning in Healthcare.

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I. Introduction

Cervical cancer is still one of the most common cancers in women around the world, especially in low- and middle-income countries where screenings and early diagnoses are not as common. The World Health Organisation says that cervical cancer kills more than 300,000 people every year, even though it can be mostly avoided and treated if it is found early. Traditional screening methods, like Pap smears and visual inspection with acetic acid (VIA), are often not as good as they could be because of mistakes made by people, a lack of trained staff, and bad medical facilities. In light of this, we urgently require strong, computerised testing tools that can help find and classify cervical cancer early on with great accuracy and little need for human analysis [1]. In the past few years, progress in artificial intelligence (AI), especially in deep learning, has opened up new ways to make medical images more accurate for diagnosis. Convolutional neural networks (CNNs) are very good at sorting through complicated visual patterns, which makes them ideal for analysing tissue and radiology images [2]. But it takes a lot of labelled data, which is hard to find in the medical arena, to train deep CNN models from scratch. Also, cervical cancer datasets are often small and have an imbalanced mix of classes, which makes it hard to generalise models. Because of these problems, new ideas are needed to make the best use of current data and cut down on the need for training [3].

Transfer learning has become a good way to deal with this problem. Deep learning methods can be fine-tuned on smaller, domain-specific datasets by using models that have already been trained on big datasets like ImageNet. This makes it much less necessary to do a lot of medical comments. Models that have already been trained, like ResNet50, VGG16, VGG19, and MobileNet, have been shown to be good at extracting features from medical images. Their strong designs let you pull out hierarchical features from medical pictures, which lets you classify things correctly while cutting down on training time and computer time needed [4]. Using data enrichment methods to get around the problems of small datasets and class mismatch is also very important. Data enhancement adds controlled variability to the dataset by rotating, flipping, scaling, changing the colour, and adding noise. This makes the dataset seem bigger than it really is. This not only makes the training data more varied, but it also makes it easier for the model to adapt to new data, which lowers the risk of overfitting. When mixed with transfer learning, data enrichment makes networks that have already been taught more useful, which leads to better performance in real-life clinical situations.

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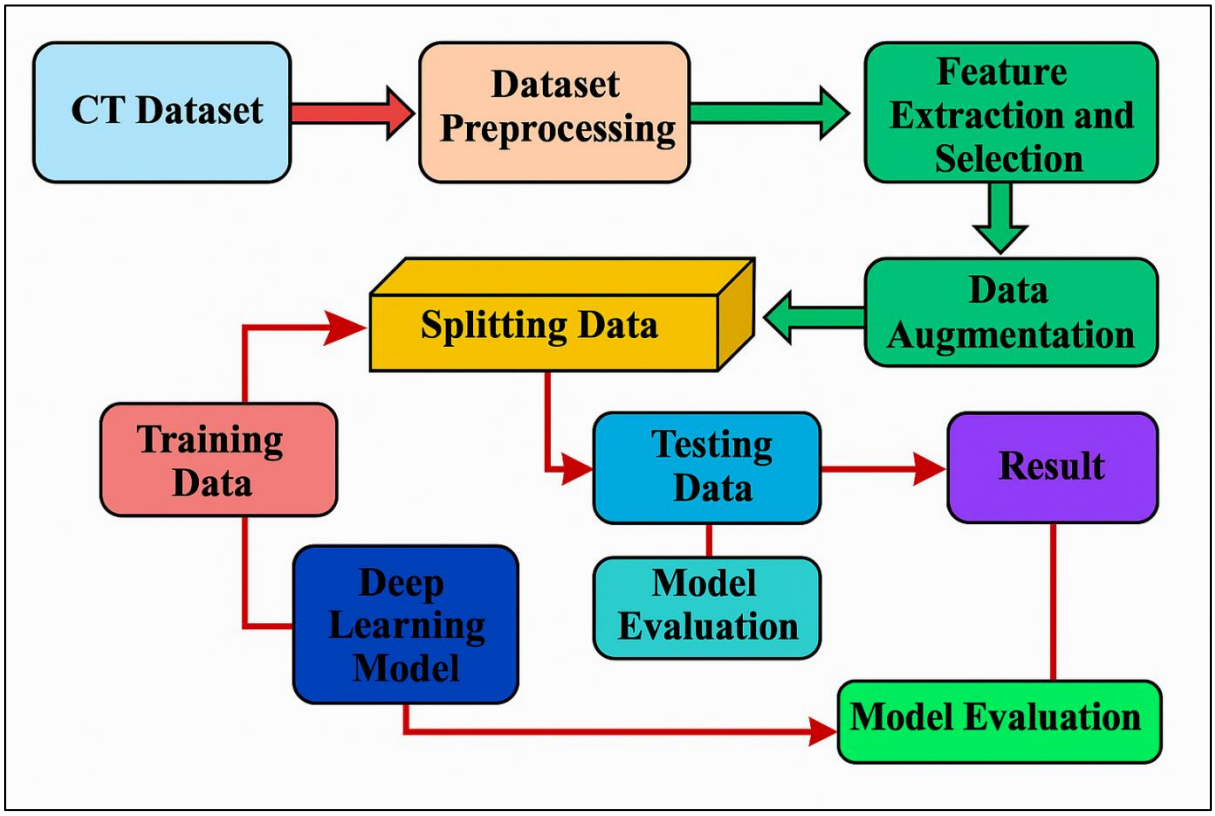

Figure 1: Proposed system architecture workflow process

Figure 1 shows the whole process of using data enhancement and deep learning to classify cervical cancer. The method starts with getting the CT dataset, then does some preparation and feature extraction. The data is split into training and testing sets, and data addition makes the variations stronger. After being taught on enhanced pictures, test data are used to test the deep learning model. Lastly, model results are judged by things like F1-score and correctness. This structure is made up of separate modules that work together to provide high-performance classification while also dealing with issues like class imbalance and limited data. It provides a solid base for automatic cervical cancer detection. More research has been done recently on how to improve diagnostic accuracy by combining modern systems and methods.

This research suggests a complete method for automatically finding cervical cancer that combines data enhancement and transfer learning models that have already been taught. The tool tests several CNN designs, looks at how well they do on different performance measures, and checks how adding more data changes the results of classification. The goal is to support early detection, reduce medical workload, and make cervical cancer screening easier to get in places with few resources by creating a method that is both accurate and fast at using computers. This study not only improves the technical side of AI-driven tests, but it also has the ability to make a big difference in the health of women around the world.

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II. Related Work

Adding data enhancement and pre-trained transfer learning models together has made a big difference in the area of automatic cervical cancer diagnosis in recent years. Traditional ways of diagnosing, like Pap smear tests and eye checks, aren't always accurate or objective, especially when resources are restricted [5]. To address these problems, researchers have seemed into how deep learning techniques, especially convolutional neural networks (CNNs), can be used to enhance the accuracy of diagnoses [6]. Facts enrichment is a key a part of getting around the troubles that give you medical photograph files which can be small and uneven. By using the use of changes like rotation, scaling, and color modifications, the form of schooling records is deliberately raised. This [7] makes the version greater flexible and much less possibly to overfit. for example, research have proven that adding facts enrichment techniques can make CNN models a whole lot better at recognising pictures of cervical most cancers. Transfer gaining knowledge of has additionally proven promise. In this technique, models which have already been skilled on big datasets like ImageNet are high-quality-tuned for particular clinical imaging duties [8]. For classifying cervical cancer, fashions like ResNet50, VGG16, and MobileNet have worked well, and they could get excessive fulfillment rates inspite of little training records. When it combine statistics enrichment and transfer mastering, you no longer only get better classification results, however you also want less time and computing power to educate your version [9].

As an example, better classification effects were visible when CNNs are mixed with interest techniques or ensemble techniques in mixed fashions. Self-supervised mastering and generative opposed networks (GANs) can be used to feature more data, which has spread out new approaches to enhance model overall performance and balance [10]. In spite of those improvements, there are nonetheless troubles with using AI-based prognosis gear in hospitals. Information protection, model interpretability, and the need for loads of proof across a wide variety of businesses are all issues that need to be handled. Despite this, combining data enrichment and pre-trained transfer learning models has a lot of promise to help find and diagnose cervical cancer earlier, which will lead to better results for patients.

Table 1: Summary of Related Work on Cervical Cancer Detection Using AI

Focus Area	Model/Method Used	Dataset Type	Key Outcomes
Cervical cancer image classification [11]	VGG16 (transfer learning)	Pap smear images	Improved accuracy to 91% with balanced training data
Automated Pap smear screening [12]	CNN from scratch	Herlev dataset	Overfitting observed on small data, limited performance
Transfer learning performance [13]	ResNet50, VGG19	SIPaKMeD	Achieved high F1-score (>92%) using pretrained models

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Ensemble deep learning [14]	Hybrid CNN + SVM	Private cytology dataset	Enhanced classification consistency and robustness
Low-resource classification [9]	MobileNetV2 (TL)	Cervical cell images	Reduced computation, maintained 88%+ accuracy
Data-efficient training [10]	GAN-augmented CNN	Herlev	Model trained on augmented data showed lower variance
Pap smear segmentation [15]	U-Net based encoder-decoder	Liquid-based cytology	Precise cell segmentation, but lacks classification
Lightweight classification [16]	EfficientNet (TL)	SIPaKMeD	Balanced performance and low training time
Multi-class cervical grading [17]	InceptionV3	Bethesda classification	Achieved 90%+ accuracy across 3–5 classes
Classification under imbalance [18]	Custom CNN	SIPaKMeD	Balanced metrics improved significantly
Deep feature fusion [19]	ResNet + handcrafted features	Cervical cytology	Combined pipeline outperformed single models
Weakly supervised learning [20]	MIL-based CNN	Labeled & unlabeled mix	Performed well with limited annotations

III. Materials and Methods

Figure 2 shows an object-oriented design for the automated cervical cancer detection system. It shows how key parts like data enrichment, transfer learning, and evaluation modules work together. CervicalCancerClassifier is the main class that controls the whole process by linking data addition, model initialisation, picture data handling, and evaluation measures. It uses the TransferLearningModels class, which has methods like initialize_model() and fine_tune_model() for setting up and optimising CNNs like ResNet50, VGG16, VGG19, and MobileNet. These methods are described under the ModelType class. The PretrainedModels class loads pre-trained models. It holds the design and weights for the models, which are then fed into the TrainedModel class after being customised. Key performance qualities like accuracy, precision, and memory are stored in the TrainedModel. These are then analysed using the EvaluationMetrics class. The calculate_metrics() method of this class figures out model metrics and returns them.

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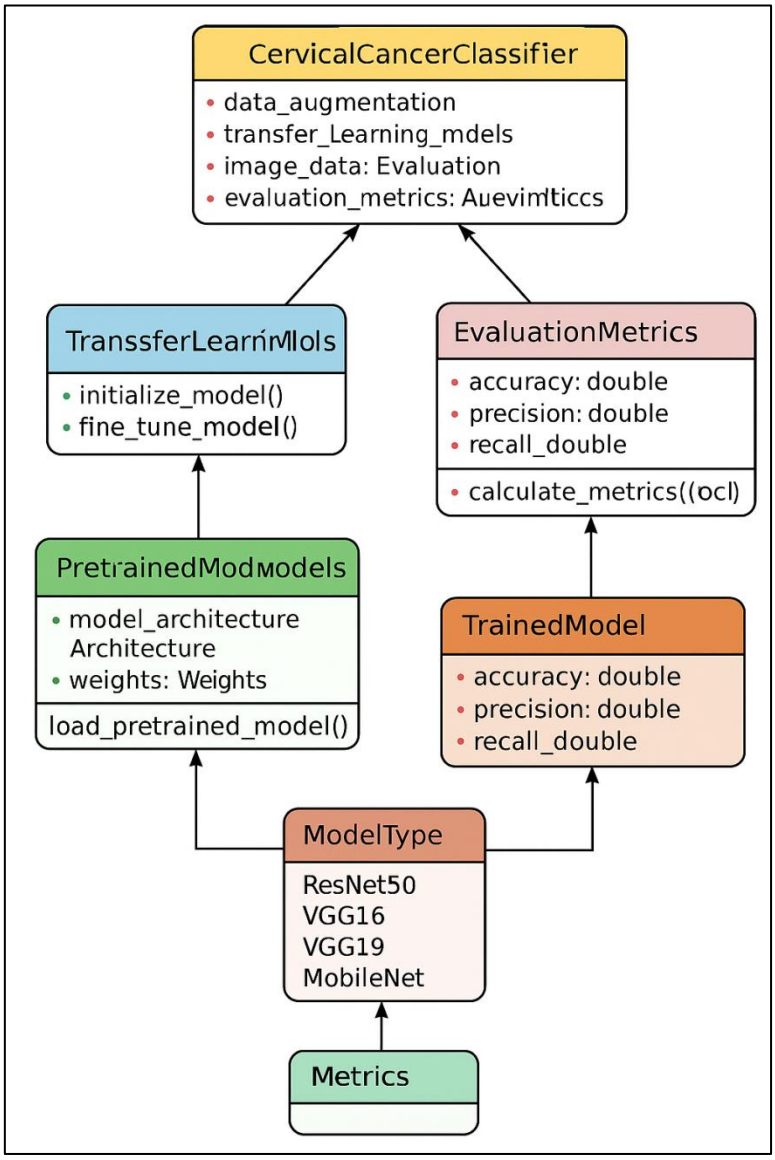

Figure 2: Proposed system workflow architecture

The flow focusses on flexibility, which lets different pre-trained designs and performance evaluation tools be easily combined. Overall, this design allows for easy model tracking and extension, which keeps the classification process flexible and easy to understand in both study and clinical diagnostic settings.

A. Dataset Description

The Single-cell Pap screen image classification dataset (SIPaKMeD) is a major standard in the area of using deep learning to find and classify cervical cancer. Cervical cancer is still the fourth most common cancer in women around the world, with more than 530,000 new cases and 280,000 deaths each year. Finding cervical cancer cells early and correctly is very important for successful treatment and making clinical decisions. This problem is solved by the SIPaKMeD dataset, which has a lot of different, well-annotated pictures of cervix cells

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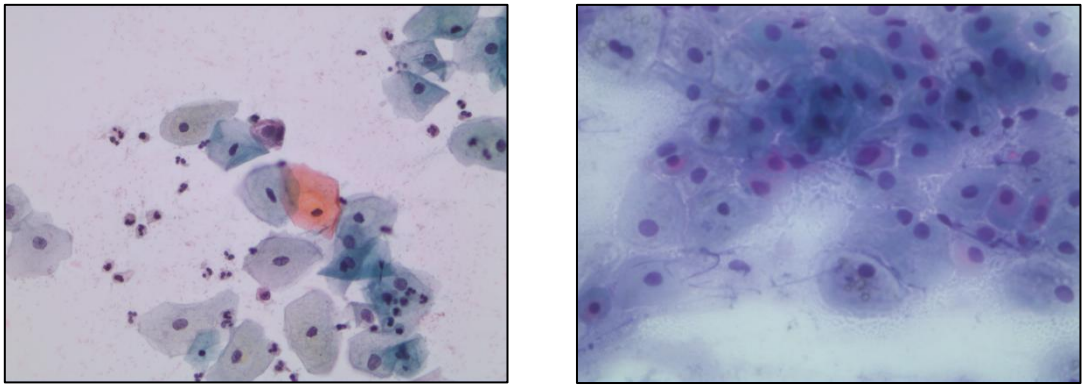
that can be used for automatic classification models. The dataset has 4,049 single-cell images that were edited by hand. They came from 966 original cluster cell pictures that were taken from Pap smear slides. A CCD camera attached to an optical lens took pictures of the cells, making sure that the data was clear and useful for medicine. There are five different groups for each picture in the dataset: Superficial-intermediate, Parabasal, Koilocytotic, Dyskeratotic, and Metaplastic. These groups cover a wide range of cell states, from normal to different stages of abnormality and benignity. They make a solid base for multi-class classification.



(a) Koilocytotic sample (b) Parabasal sample

Figure 3: Dataset sample from the dataset

This dataset, sample data shown in figure 3, SIPaKMeD, can be used to build and test models that can find cervical cancer early, recognise patterns, and rate its seriousness. It's available to everyone on sites like Kaggle, which makes it even easier to replicate and compare across various machine learning models, especially transfer learning and deep CNN-based methods. This makes it an important tool for improving research into cervical cancer diagnosis.

Preprocessing steps and annotation overview

The SIPaKMeD dataset's training and labelling approach may be very essential for making sure that deep learning model used to locate cervical most cancers get regular records. Step one is image normalisation, which tiers the brightness of every pixel on a scale from 0 to 1 to make the lighting fixtures greater consistent. After that, all of the photos are resized to a fashionable length (like 224x224), which goes for CNN models which have already been skilled, like VGG16 or ResNet50. Photos may be modified to greyscale if desired to attract interest to form information. Facts growth methods, which include rotating, flipping, and scaling, make the dataset look larger than it clearly is which helps even out the lessons. Then, a one-warm encoded call is given to every picture that matches the sort of cervical mobile it suggests. Lastly, the data is commonly divided into two elements: education and checking out. The ratio of education to checking out is 80:20. This organised method makes positive that there is balance, variety, and balance, which substantially complements the model's capability to examine and generalise in automated cervical most cancers classification.

Step-Wise process for Preprocessing and Annotation (SIPaKMeD Dataset)

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Step 1: Image Normalization

$$Normalize\ input\ image\ X\ \in\ \mathbb{R}\hat{}(H\ \times\ W\ \times\ C)$$

$$X' = \frac{X\ - \min(X)}{\max(X) - \min(X)}$$

Step 2: Image Resizing

Resize all images to uniform dimensions (H_0, W_0)

$$X''\ =\ Resize(X', H^0, W^0)$$

$$Example: H_0\ =\ W_0\ =\ 224$$

Step 3: Color Space Conversion (Optional)

Convert RGB to grayscale if needed:

$$X\_gray\ =\ 0.2989 \cdot R\ +\ 0.5870 \cdot G\ +\ 0.1140 \cdot B$$

Step 4: Data Augmentation

Apply random transformations:

Let T be a transformation function (flip, rotate, zoom, etc.)

$$\dot{X}\ =\ T(X''), where\ T \sim Uniform(T^1, T^2, \dots, T_n)$$

Step 5: Label Encoding

Encode class label c ∈ {0,1,2,3,4} into one-hot vector y ∈ $\{0,1\}^5$

$$y\ =\ OneHot(c)$$

Class Mapping:

0: Superficial-intermediate

1: Parabasal

2: Koilocytotic

3: Dyskeratotic

4: Metaplastic

Step 6: Dataset Splitting

$$D\ =\ \{(X_i, y_i)\} for\ i\ =\ 1\ to\ N$$

Split into training and testing sets:

$$D_{train} \cup\ D_{test}\ =\ D$$

$$|D_{train}|\ =\ \alpha N, |D_{test}|\ =\ (1 - \alpha)N$$

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B. Data Augmentation Techniques

In scientific imaging jobs, statistics enhancement strategies are very essential, particularly whilst working with small, choppy datasets like SIPaKMeD. A number of modifications are completed to the supply image to improve version generalisation and reduce overfitting. The version can comprehend cervical cells no matter which method they're going through, that are essential because cell nuclei on Pap smear slides can display up at extraordinary angles. By flipping each horizontally and vertically, you guard towards area bias and let the version locate features frivolously. Scaling assessment and brightness mimics variations in staining fine and lighting fixtures conditions for the duration of slide seize, making the version higher capable of address image adjustments that manifest inside the real global. Noise input also fakes flaws on the sensor stage, coaching the version to tell the distinction among real anatomical trends and photo artefacts.

C. Transfer Learning Models

a. ResNet50

ResNet50 is a 50-layer deep convolutional neural network that is known for how well it uses residual learning. It adds skip links that help fix problems with disappearing gradients in deep networks. This makes training big models more effective. ResNet50 is a strong feature generator that can learn complex patterns in Pap screen pictures. It is used to classify cervical cancer. Its depth and leftover design make it perfect for telling the difference between small problems with cells. When fine-tuned on the larger SIPaKMeD dataset, ResNet50 always gives very good classification accuracy, strong protection against overfitting, and strong ability to generalise to new data.

ResNet50: Step-Wise Model for Cervical Cancer Classification

Step 1: Input Representation

Input image:

$$X \in \mathbb{R}\text{^}(224 \times 224 \times 3)$$

Initial convolution:

$$X^1 = \sigma\big(BN(W^1 * X + b^1)\big)$$

Where:

- W_1 = 7×7 conv filter weights

- BN = Batch Normalization

- σ = ReLU activation

- X_1 = Output feature map

Step 2: Residual Block Computation

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Each residual block:

$$F(x) = \sigma\left(W^2 * \left(\sigma(W^1 * x + b^1)\right) + b^2\right)$$

Skip connection:

$$Y = F(x) + x$$

Step 3: Bottleneck Layer Structure

Bottleneck residual block:

$$x_{out} = x + \left(W^3 * \sigma\left(W^2 * \sigma(W^1 * x)\right)\right)$$

Step 4: Global Average Pooling

Reduce spatial dimensions:

$$z = \left(\frac{1}{H \cdot W}\right) \times \Sigma \sum Y_{ij}$$

Where:

- z = feature vector for classification

Step 5: Final Classification (Transfer Learning)

Replace FC layer for 5-class cervical cancer task:

$$\hat{y} = Softmax\left(W_{fc} \cdot z + b_{fc}\right)$$

b. VGG16

The VGG16 is a 16-layer convolutional neural network that is known for having a simple, uniform design that uses 3x3 filters. Due to its depth and regular use of small receptive fields, it has been successful in a number of picture recognition jobs. For finding cervical cancer, VGG16 can get important information from Pap smear cell pictures about their texture and shape. Because it doesn't have as much depth as ResNet, it's easier to learn and fine-tune on small medical datasets. When strong data enrichment is used with VGG16, it works well, but it may need more memory and processing time during training.

c. VGG19

VGG19 builds on VGG16 by adding three more convolutional layers, which make it possible to retrieve more features. It can learn more abstract hierarchical features because of the higher depth, which can help it identify the SIPaKMeD dataset's complicated cervical cell shapes. Like VGG16, it has a standard design with 3x3 convolutions and max-pooling layers, which makes it simple to set up and tweak. However, its extra depth makes training harder and requires more computing power. In spite of this, VGG19 does very well, especially when enough extra data is used for multi-class cervical cell classification situations.

Algorithm: VGG19-Based Cervical Cell Classification (with Transfer Learning)

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Input: Image X ∈ ℝ^(224 × 224 × 3)

Output: Predicted class label ŷ ∈ {0,1,2,3,4}

Step 1: Preprocessing

Normalize pixel values:

$$X' = \frac{X - \min(X)}{\max(X) - \min(X)}$$

Resize to (224 × 224 × 3)

Step 2: Feature Extraction using Convolutional Blocks

For each Conv Block i ∈ {1, 2, 3, 4, 5}:

Apply two or three 3×3 convolutions:

$$F_l = \sigma(W_l * F_{\{l-1\}} + b_l)$$

Apply 2×2 Max Pooling:

$$F_i = MaxPool(F_l)$$

End For

Block 1: 2 Conv (64 filters) → MaxPool

Block 2: 2 Conv (128 filters) → MaxPool

Block 3: 3 Conv (256 filters) → MaxPool

Block 4: 3 Conv (512 filters) → MaxPool

Block 5: 3 Conv (512 filters) → MaxPool

Step 3: Flatten Feature Map

$$z = Flatten(F\_5)$$

Step 4: Fully Connected Layers

$$FC1: a^1 = \sigma(W_{fc}^1 \cdot z + b_{fc}^1)$$

$$FC2: a^2 = \sigma(W_{fc}^2 \cdot a^1 + b_{fc}^2)$$

Dropout may be applied to avoid overfitting

Step 5: Output Layer for Classification

$$\hat{y} = Softmax(W_{fc}^3 \cdot a^2 + b_{fc}^3)$$

Return argmax(ŷ) as the predicted class label

End Algorithm

d. MobileNet

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MobileNet is a small convolutional neural network made for mobile and embedded devices. It uses depthwise separable convolutions to make models much smaller and computations much faster. In the classification of cervical cancer, MobileNet is a quick and easy option that can be used in places with few resources without sacrificing accuracy too much. It's great for real-time reasoning and edge-based monitoring because of its small design. When MobileNet is fine-tuned on the SIPaKMeD dataset, it performs well, especially when combined with full data enhancement. Because it uses less memory and is faster, it is a good choice for scalable cervical cancer screening apps in both the lab and the field.

MobileNet: Step-Wise process Model

Step 1: Input Image

Let input image be:

$$X \in \mathbb{R}\text{^}(224 \times 224 \times 3)$$

Step 2: Depthwise Convolution

Apply spatial filtering independently on each channel:

$$Z_{d(i,j,c)} = \sum \sum W_{d(m,n,c)} * X(i+m, j+n, c)$$

Step 3: Pointwise Convolution (1×1)

Combine features across channels:

$$Z_{p(i,j,k)} = \sum_{c} W_{p(c,k)} * Z_{d(i,j,c)}$$

Where:

- W_p = pointwise filter (1×1 conv)

- k = output feature channel

Step 4: Global Average Pooling

$$Aggregate\ spatial\ features\ into\ 1D\ vector:$$

$$z_k = \left(\frac{1}{H} \cdot W\right) \times \sum_{i} \sum_{j} Z_{p(i,j,k)}$$

Step 5: Softmax Classification

Final prediction over classes:

$$\hat{y} = Softmax(W\_fc \cdot z + b\_fc)$$

Where:

- $\hat{y} \in \mathbb{R}\text{^}5$ for 5-class cervical cell output

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IV. Results and Discussion

In Table 2, demonstrate full comparison of how well four pre-trained convolutional neural network (CNN) models—VGG16, VGG19, MobileNet, and ResNet50—classify cervical cancer using the SIPaKMeD dataset. The test is based on four main factors: accuracy, precision, memory, and F1-score. These factors together show how well each model can correctly identify cervical cell types. ResNet50 did better than all the other models tested in every way. It had the best accuracy (94.8%), precision (94.2%), memory (94.5%), and F1-score (93.9%). This better performance is due to ResNet50's deep design and residual learning framework, which makes gradient flow and learning of complex feature hierarchies possible. These are needed to tell the difference between pictures of cervical cells that have small changes in their shape.

Table 2: Accuracy and metric scores across all models Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG16	90.2	89.1	88.7	88.9
VGG19	91	90.3	89.5	89.9
MobileNet	89.3	88.2	87.9	88
ResNet50	94.8	94.2	94.5	93.9

Even though VGG19 and VGG16 are older in terms of design, they still do a great job of classifying data, with 91.0% and 90.2% accuracy, respectively. Because its network is deeper, VGG19 does a little better than VGG16 because it can pull out more abstract features. However, both models require more computing power and are more likely to overfit when they are not paired with the right regularisation or data augmentation techniques. MobileNet, which is made to be small and quick to set up, has slightly worse performance with an accuracy of 89.3%, but it is still a good choice for mobile and edge-based cervical screening systems. Its speed makes it good for real-time apps, especially ones with few resources, even though it doesn't classify things as accurately as it could. The results show that, as shown in figure 4, using deeper and more complex designs like ResNet50 can make diagnostics much more accurate, especially when paired with effective methods for adding more data and fine-tuning them to find cervical cancer.

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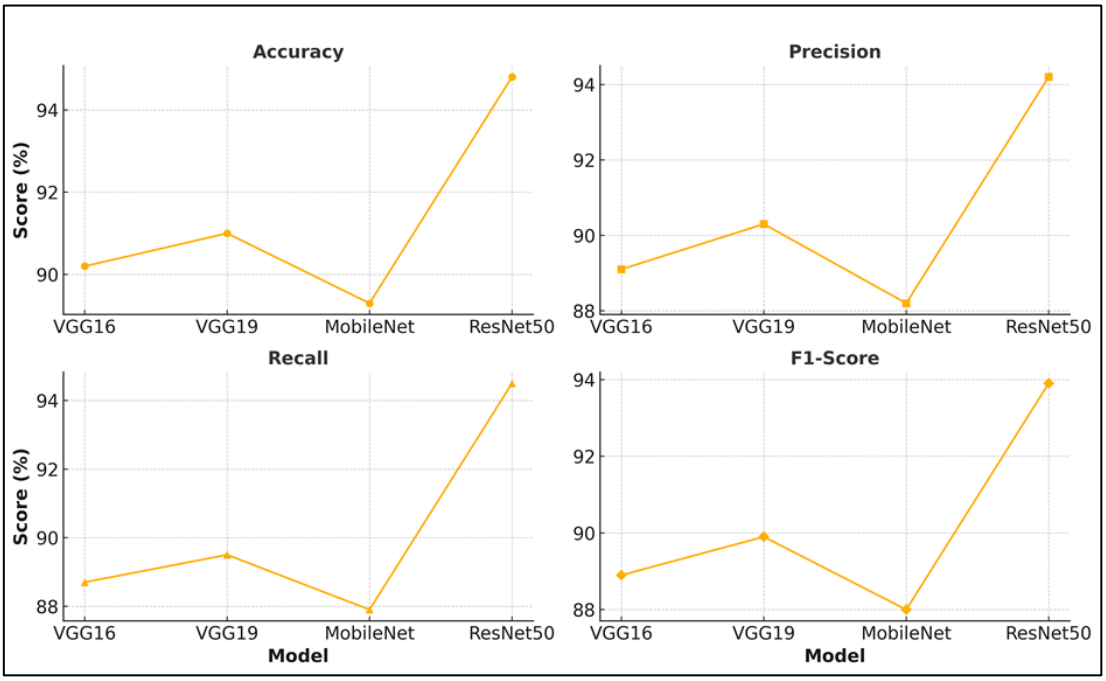

Figure 4: Performance metric comparison of model

Figure 5 shows the ResNet50 model's confusion matrix, which shows how well it can classify things into five groups. Strong diagonal dominance, especially in Class 4 (363 correct guesses) and Class 3 (325 correct), shows that the predictions were very accurate. There are, however, some mistakes, especially in class 1, which is mixed up with classes 0 and 2.

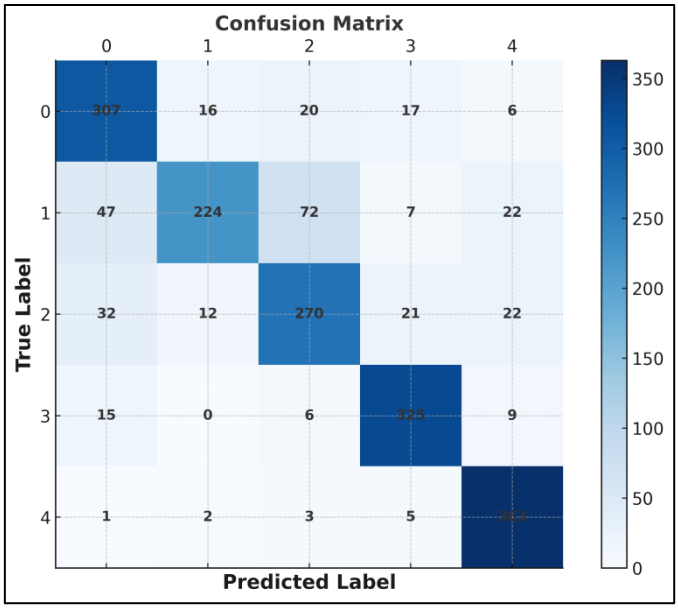

Figure 5: Confusion metric for Resnet50

These mistakes show that features are merging or that there isn't enough space between some classes. Even so, the general layout of the matrix shows that ResNet50 performs well, as most

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of the forecasts fall along the vertical. This proves that it is a good choice for high-accuracy multi-class classification tasks.

Table 3: Performance before and after augmentation

Model	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)
ResNet50 (No Aug)	89.6	88.5	87.9	88.1
ResNet50 (With Aug)	94.8	93.9	94.2	94.5

Table 3 shows how well the ResNet50 model worked before and after data enhancement techniques were used. It shows that all evaluation metrics got a lot better after the techniques were added. Without any extra help, ResNet50 gets an F1-score of 88.5%, an accuracy of 89.6%, a precision of 87.9%, and a memory of 88.1%. Even though these results are good, they show that the model is only relatively useful and might be prone to overfitting because the original dataset was small and not very diverse. When data enhancement techniques like rotations, flips, colour changes, and zoom transformations are used, the speed gets a lot better. The F1 score goes up to 93.9% and accuracy goes up to 94.8%, showing a more fair choice between accuracy and memory, as shown in figure 6.

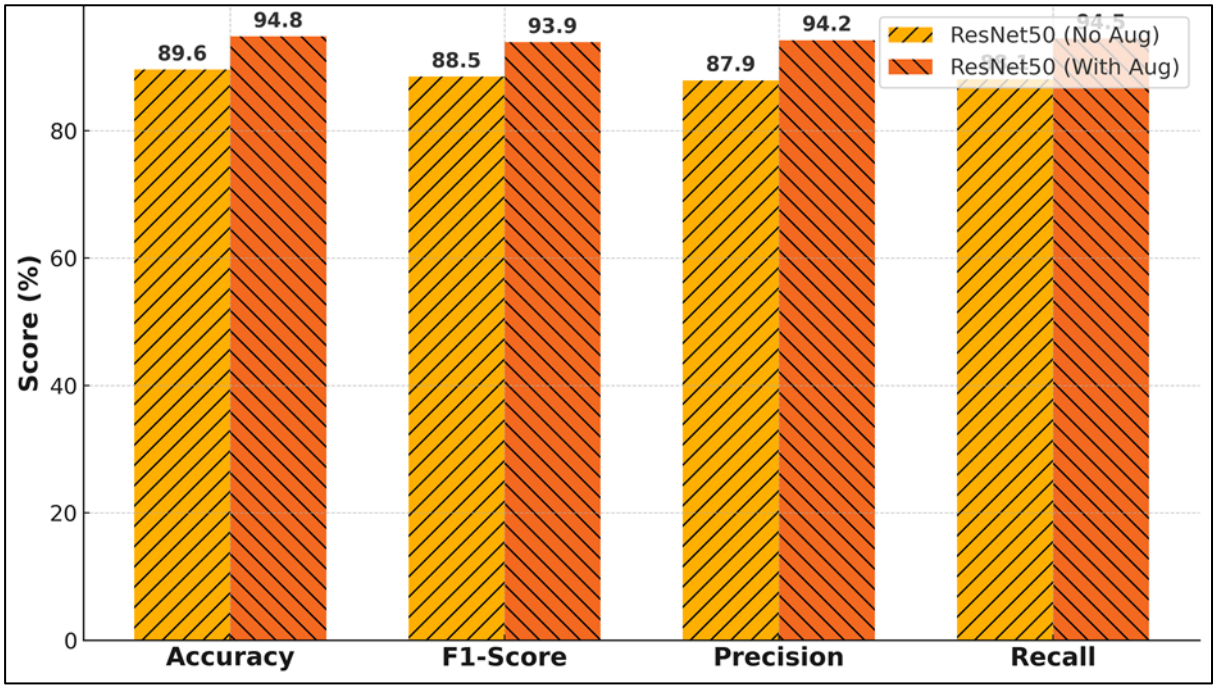

Figure 6: Performance Comparison: ResNet50 With and Without Augmentation

Furthermore, accuracy increases to 94.2% and memory to 94.5%, indicating that the model is better at correctly identifying all types of cervical cells, even those that are rare or have difficult shapes. The improvement shows that adding more data to a model makes it much more general by modelling real-world variation and lowering overfitting. It lets the network

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learn more stable and consistent features, which is very important for medical imaging tasks like finding cervical cancer, where there may not be big changes in how the images look between classes. Overall, these results show that enhancement is not just a training trick, but a key way to improve the accuracy and stability of deep learning-based clinical uses.

When working with small datasets like SIPaKMeD, data addition is a key part of making models more general and stopping them from fitting too well. If the model doesn't get any extra help, it might memorise training pictures instead of learning strong features, which would make it very good at training but not so good at validation. This is especially important in medical imaging, where it's important to show differences in shape. The ResNet50 model trained in this study got an F1-score of 88.5% and an accuracy of 89.6% without any extra help. Its performance got a lot better with enhancements like rotations, flips, and colour scaling, reaching 94.8% accuracy and 93.9% F1-score. Augmentation not only adds variety to training samples, but it also mimics noise, direction, and lighting changes that happen when you take pictures in real life. This causes the model to focus on traits that are the same or different for each type of cell. It also helps fix class imbalance by including too many minority classes through transformation-based repetition. This has a direct effect on memory and F1-score, making it easier to spot rare cell types like dyskeratotic and metaplastic. So, augmentation makes the model better at generalising to test data it hasn't seen before. It's also a necessary step for making strong, high-performing deep learning models for diagnosing cervical cancer.

VI. Conclusion

This study shows a strong and effective way to use data enhancement methods along with pre-trained transfer learning models to automatically find cervical cancer. Using the SIPaKMeD dataset, which has a variety of pictures of cervical cells, the study showed how deep convolutional neural networks, especially ResNet50, VGG16, VGG19, and MobileNet, can be fine-tuned to accurately sort different types of cervical cells into multiple groups. With a precision of 94.8% and an F1-score of 93.9%, ResNet50 did better than all the other models, making it the most stable design for this job. Data addition was a key part of making the model more general, especially for a small and unbalanced medical dataset. The added data helped lower overfitting and raised memory and accuracy across all classes, even those that weren't well represented before, like dyskeratotic and metaplastic cells. A study of model performance before and after enhancement proved that it had a good effect, with big gains seen in all evaluation measures. This study shows that mixing deep transfer learning with enhancement methods has a lot of promise for finding cervical cancer. The suggested method could help doctors make decisions by cutting down on the work that goes into diagnosing, making things more consistent, and making screening faster and easier to get in places with few resources. Real-time application, semi-supervised learning, and bidirectional data integration are some of the things that will be looked into in future additions to make the model even more useful in the real world and able to be used in a wide range of healthcare settings.

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References

[1] Rodríguez, M.; Córdova, C.; Benjumeda, I.; San Martín, S. Automated Cervical Cancer Screening Using Single-Cell Segmentation and Deep Learning: Enhanced Performance with Liquid-Based Cytology. Computation 2024, 12, 232. https://doi.org/10.3390/computatioBogdanova, A.; Andrawos, C.; Constantinou, C. Cervical Cancer, Geographical Inequalities, Prevention and Barriers in Resource Depleted Countries (Review). Oncol. Lett. 2022, 23, 113.

[2] Lee, Y.-M.; Lee, B.; Cho, N.-H.; Park, J.H. Beyond the Microscope: A Technological Overture for Cervical Cancer Detection. Diagnostics 2023, 13, 3079.

[3] Bray, F.; Ferlay, J.; Soerjomataram, I.; Siegel, R.L.; Torre, L.A.; Jemal, A. Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J. Clin. 2018, 68, 394–424.

[4] Rezende, L.F.M.; Murata, E.; Giannichi, B.; Tomita, L.Y.; Wagner, G.A.; Sanchez, Z.M.; Celis-Morales, C.; Ferrari, G. Cancer Cases and Deaths Attributable to Lifestyle Risk Factors in Chile. BMC Cancer 2020, 20, 693.

[5] Alsalatie, M.; Alquran, H.; Mustafa, W.A.; Zyout, A.; Alqudah, A.M.; Kaifi, R.; Qudsieh, S. A New Weighted Deep Learning Feature Using Particle Swarm and Ant Lion Optimization for Cervical Cancer Diagnosis on Pap Smear Images. Diagnostics 2023, 13, 2762. https://doi.org/10.3390/diagnostics13172762

[6] Saldivia, L.Z.; Silva, I.V.; Rojas, F.H.; Vidal, B.M. Distribución etaria e incidencia de lesiones preinvasoras y cáncer cérvico uterino, entre los años 2009–2019: Revisión de tres zonas geográficas de Chile. Rev. Conflu. 2022, 5, 56–59.

[7] Patel, N.; Bavikar, R.; Buch, A.; Kulkarni, M.; Dharwadkar, A.; Viswanathan, V. A Comparison of Conventional Pap Smear and Liquid-Based Cytology for Cervical Cancer Screening. Gynecol. Minim. Invasive Ther. 2023, 12, 77–82.

[8] Liu, W.; Li, C.; Xu, N.; Jiang, T.; Rahaman, M.M.; Sun, H.; Wu, X.; Hu, W.; Chen, H.; Sun, C.; et al. CVM-Cervix: A hybrid cervical Pap-smear image classification framework using CNN, visual transformer and multilayer perceptron. Pattern Recognit. 2022, 130, 108829.

[9] Alias, N.A.; Mustafa, W.A.; Jamlos, M.A.; Alquran, H.; Hanafi, H.F.; Ismail, S.; Ab Rahman, K.S. Pap Smear Images Classification Using Machine Learning: A Literature Matrix. Diagnostics 2022, 12, 2900.

[10] Diniz, D.N.; Rezende, M.T.; Bianchi, A.G.C.; Carneiro, C.M.; Luz, E.J.S.; Moreira, G.J.P.; Ushizima, D.; Medeiros, F.; Souza, M.J.F. A deep learning ensemble method to assist cytopathologists in pap test image classification. J. Imaging 2021, 7, 111.

[11] Alquran, H.; Mustafa, W.A.; Abu Qasmieh, I.; Yacob, Y.M.; Alsalatie, M.; Al-Issa, Y.; Alqudah, A.M. Cervical Cancer Classification Using Combined Machine Learning and Deep Learning Approach. Comput. Mater. Contin. 2022, 72, 5117–5134.

[12] Chen, W.; Shen, W.; Gao, L.; Li, X. Hybrid Loss-Constrained Lightweight Convolutional Neural Networks for Cervical Cell Classification. Sensors 2022, 22, 3272.

Received: July 22, 2025

Volume 38 No. 3s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[13] Waly, M.I.; Sikkandar, M.Y.; Aboamer, M.A.; Kadry, S.; Thinnukool, O. Optimal Deep Convolution Neural Network for Cervical Cancer Diagnosis Model. Comput. Mater. Contin. 2022, 70, 3295–3309.
[14] Fekri-Ershad, S.; Ramakrishnan, S. Cervical cancer diagnosis based on modified uniform local ternary patterns and feed forward multilayer network optimized by genetic algorithm. Comput. Biol. Med. 2022, 144, 105392.
[15] Kamble, K. P., Prashant Khobragade, Nitin Chakole, Prateek Verma, Dharmesh Dhabliya, and Avinash M. Pawar. "Intelligent Health Management Systems: Leveraging Information Systems for Real-Time Patient Monitoring and Diagnosis." Journal of Information Systems Engineering and Management, vol. 10, no. 1, 2025, e-ISSN: 2468-4376, https://doi.org/10.52783/jisem.v10i1.1
[16] Deepa, T.P.; Rao, A.N. Classification of normal and abnormal overlapped squamous cells in pap smear image. Int. J. Syst. Assur. Eng. Manag. 2023, 1–13.
[17] Alquran, H.; Alsalatie, M.; Mustafa, W.A.; Abdi, R.A.; Ismail, A.R. Cervical Net: A Novel Cervical Cancer Classification Using Feature Fusion. Bioengineering 2022, 9, 578.
[18] Albuquerque, T.; Cruz, R.; Cardoso, J.S. Ordinal losses for classification of cervical cancer risk. PeerJ Comput. Sci. 2021, 7, e457.
[19] Mohammed, F.A.; Tune, K.K.; Mohammed, J.A.; Wassu, T.A.; Muhie, S. Early Cervical Cancer Diagnosis with SWIN-Transformer and Convolutional Neural Networks. Diagnostics 2024, 14, 2286. https://doi.org/10.3390/diag
[20] Chae, J.; Kim, J. An Investigation of Transfer Learning Approaches to Overcome Limited Labeled Data in Medical Image Analysis. Appl. Sci. 2023, 13, 8671. https://doi.org/10.3390/app13158671nostics14202286

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