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Precision Medicine in Gastroenterology: An AI-Powered Polyp Detection for Advanced Colonoscopy Diagnostics Using Deep Learning

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ABSTRACT:
The use of artificial intelligence (AI) in medical processes, especially colonoscopies, has made big steps forward in precision medicine in gastroenterology. Using deep learning techniques, this abstract looks at how an AI-powered polyp detection system could change the way advanced colonoscopy tests are done. Gastric endoscopists usually do the check by hand, which can lead to mistakes and missed problems. Modern deep learning methods are used in the suggested system to look at endoscope images. This makes polyp detection more accurate and faster. A lot of different types of colonoscopy images are used to train the deep learning model, which learns complex patterns and traits linked to polyps. There are a lot fewer false rejections and fake positives because the AI system is so sensitive and detailed. Adding real-time AI to colonoscopies gives gastroenterologists more power by giving them immediate and accurate feedback that helps them make quick decisions. This makes diagnoses more accurate generally in addition it also makes the work of healthcare workers easier. Also, the system changes and adapts over time by constantly learning from new data and ideas further applying those to improve its performance. This AI-powered polyp detection method in gastroenterology marks the start of a new era of personalized and accurate diagnoses, which is in line with the ideas behind precision medicine. One effect that could happen is the early identification of colon problems, which could improve patient results and lower the cost of healthcare. This brief talks about the benefits and risks of using AI in colonoscopy and how it can help improve precise medicine in the area of gastroenterology. In present work, pre-trained deep learning models viz. VGG19, DenseNet169, InceptionV3, MobileNetV3, and ResNet101 are explored and comparative analysis of performance of these models is discussed with interpretations.

I. Introduction

Precision medicine is a new way of thinking about healthcare that focuses on creating personalized and focused treatments for each patient based on their unique traits. With the help of cutting-edge technologies, especially artificial intelligence (AI), this idea has received a lot of support in the area of gastroenterology. This introduction looks at how an AI-powered polyp detection system for improved colonoscopy tests that uses advanced deep learning techniques could change the way diagnosis and treatment are practiced. Traditionally, gastroenterologists have been the ones who do the eye check of the colon during colonoscopy, which is a key part of finding and preventing intestinal problems [1]. However, this process is done by hand and obviously it has some demerits that come with it, like the chance of human mistake and missing detections. When AI is used in colonoscopy, it tries to get around these problems by using deep learning to make polyp detection more accurate and faster. A deep learning [2] model that was trained on a large and varied set of colonoscopy pictures is at the heart of this new idea. The model goes through a lot of training to learn the complex patterns and traits that are linked to polyps. This helps it find smaller health problem indicators that a practitioner might miss. Deep learning is useful in this situation because it can look through huge amounts of data and find useful patterns and information that makes tests more accurate.

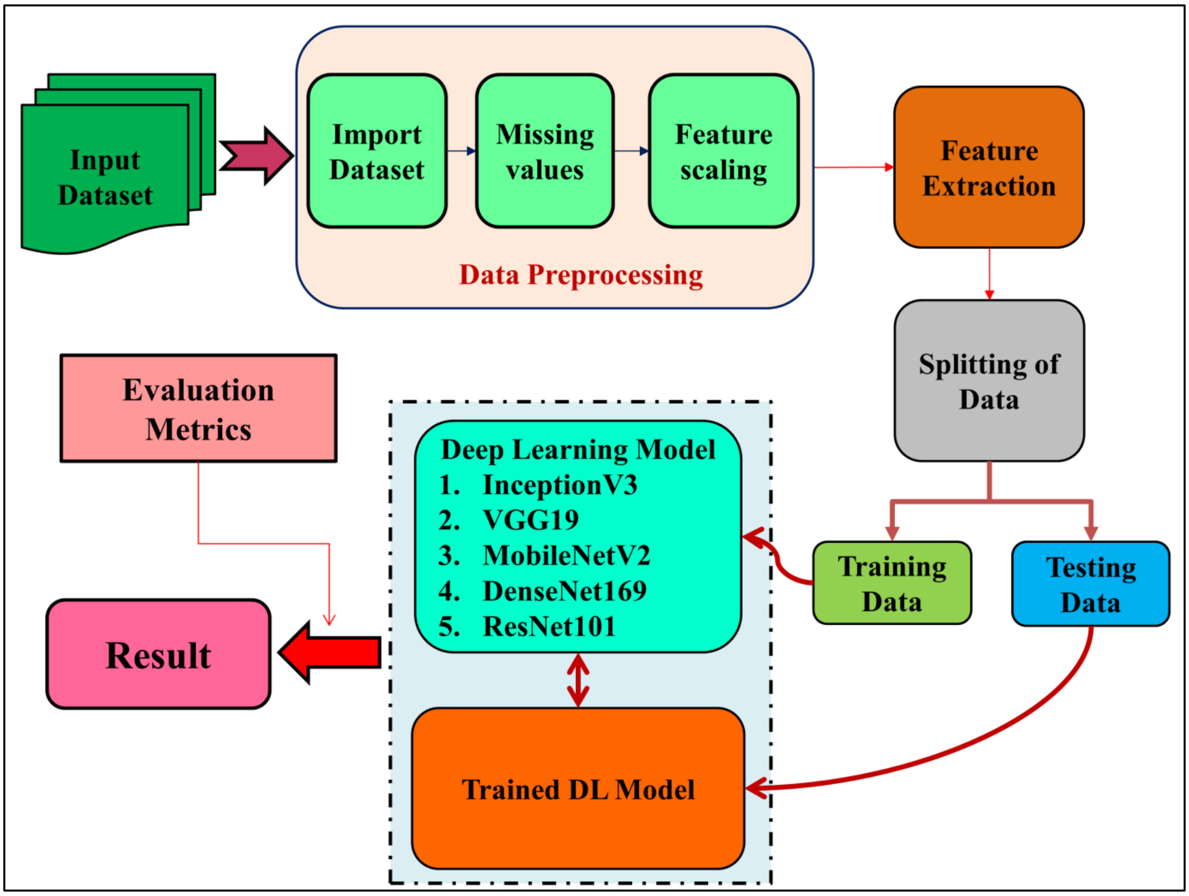

Figure 1: Systematic architecture of Proposed System

The proposed deep learning solution is very sensitive and specific, which means that it reduces the number of false failures and false positives. This higher level of accuracy makes colonoscopy better at diagnosing problems and also makes it less likely that needless procedures will be done or that abnormalities will be missing. Since real-time AI help is now used during colonoscopies, it has completely changed how gastroenterologists do tests. The AI [3], [4] system's instant feedback gives healthcare workers more power, which helps them make decisions more quickly and could lead to better patient results. The AI-powered polyp recognition system is also not fixed; it is meant to change and adapt by learning new things all the time. This dynamic feature [4] lets the model keep up with new trends and changes in polyp traits, which guarantees that performance will keep getting better over time. The system adds more data as it becomes available, which helps it understand things better and make its diagnoses more accurate. This ability to change goes along with the ideas of precision medicine, which aims to make medical choices and treatments fit the unique needs of each patient. Adding AI [5] to colonoscopy has effects that go beyond just making it more accurate. Being able to learn and change means that the system could also help find colon problems early on, possibly finding precancerous tumors when they can be best treated. This has huge effects on how well patients do and can help lower the costs of new treatments by a large amount. Adding AI-powered tests to gastroenterology is another example of how healthcare is changing all the time. Combining the ideas of precision medicine with cutting edge technologies like deep learning is a big step toward better, more personalized, and faster care for patients [6]. When AI and

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colonoscopy work together, they do more than just make a screening tool better; they also mark a shift toward a more proactive and focused approach to gut health.

II. Related work

Precision Medicine [7] has been used in gastroenterology, which has led to a lot of study that aims to improve how to diagnose and treat each patient. As the field grows, one of the most important things to look into is how to use artificial intelligence (AI) and deep learning in medical processes, especially when it comes to colonoscopies. This part goes into detail about the linked work that made it possible to create an AI-powered polyp detection system for improved colonoscopy surgery. Recent studies [8] have pointed out the problems with standard screening methods, like the fact that mistakes can happen and some problems might not be found. Even though gastroenterologists are very skilled, they may miss small problems, which can cause evaluation and treatment to take longer than expected. In answer to these problems, academics have looked to AI as a possible way to help healthcare workers do their jobs better. Several studies have looked into whether and how well deep learning algorithms can be used to find polyps in test image samples. The main goal has been to make models that can automatically look at endoscopy photos, find polyps with high accuracy, and reduce the number of false positives. Studies that show deep learning can do better than standard computer-aided detection (CAD) systems in terms of accuracy and speed are important additions to this field.

Creating large [9] and varied datasets for training deep learning models is an important part of linked work. These files have a lot of different colonoscopic pictures that show polyps in a lot of different shapes, sizes, and places. It is very important that these datasets are very large so that the AI system can work well in a variety of clinical situations and find problems that may show up in different ways. Researchers have worked together to make uniform datasets that make it easier to get the same results from different AI models and make fair comparisons between them. Additionally, research has looked into how to use real-time AI to help with colonoscopies. Utilizing AI models that can give gastroenterologists immediate feedback while they perform exams is a part of this. These AI [10], [11] systems are meant to help doctors make better decisions during procedures by giving them instant information about whether a polyp is present or not. A lot of related work has been done on how to make AI work seamlessly with the hospital process. This work has looked at how to use these technologies in real medical settings. The state of the art has been greatly improved by the work of diverse teams that include gastroenterologists, computer scientists, and image experts. These [12] groups work together to create and test AI models, making sure they meet strict criteria for clinical usefulness and dependability. Because this joint process is iterative, AI algorithms can be constantly tweaked and improved, which pushes the limits of what is possible in terms of polyp identification accuracy. In addition to the scientific parts, linked work has also looked at the legal and moral issues that come up when AI is used in gastroenterology. A lot of important things need to be talked about before these technologies can be used in clinical practice. These include patient consent, data protection, and making rules for processes that use AI [13]. Finally, the linked work in Precision Medicine in Gastroenterology, especially in the area of using AI to find polyps for more improved colonoscopy diagnoses, shows a wide range of study projects. Researchers are working together to make testing methods more accurate and useful. They are doing things like building strong deep learning models, standardizing datasets, and exploring the use of real-time AI help. Working together with people from different fields and thinking about both technical and moral issues show how thorough the method needs to be to start the era of AI-enhanced precision care in gastroenterology.

Table 1: Summary of related work

Method	Database Used	Finding	Limitation	Scope
Deep Learning Algorithms [14]	Diverse Colonoscopy Images	Outperforms traditional CAD systems, superior accuracy	Limited to available data, potential bias in training datasets	Generalization across diverse clinical scenarios

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Real-time AI Assistance [15]	Clinical Workflow Integration	Immediate feedback aids decision-making during procedures	Technological infrastructure requirements, potential disruption	Seamless integration into clinical practice, improved efficiency
Collaborative Multidisciplinary Teams [16]	Varied Expertise Collaboration	Synergistic development and validation of AI models	Resource-intensive, coordination challenges	Continuous refinement and improvement of AI algorithms
Standardized Datasets [17]	Diverse Polyp Morphologies	Facilitates reproducibility and fair model comparisons	Availability and representativeness of datasets	Ensures robust model training, enhances generalization
Ethical Considerations [18]	Patient Consent, Data Privacy	Addresses ethical and regulatory aspects	Balancing patient privacy with data utilization	Establishing guidelines for AI-assisted procedures
Improved Sensitivity [19]	Extensive Clinical Validation	Enhances sensitivity, reducing false negatives	Varied patient populations, potential over-reliance on technology	Early detection of colorectal abnormalities, improved outcomes
Iterative Development [20]	Continuous Refinement	Iterative process for ongoing improvement	Resource and time-intensive, potential for model overfitting	Adaptable models evolving with emerging trends

III. Methodology

In advanced colonoscopy diagnostics, the AI-powered polyp detection system uses four cutting-edge convolutional neural network (CNN) architectures: VGG19, DenseNet169, InceptionV3, and MobileNetV3. ResNet101 is also used. The training and testing sample is made up of a wide range of colonoscopy images showing polyps of different shapes, sizes, and positions. Fine-tuning each pre-trained CNN architecture on the colonoscopy picture dataset is part of the training process. This lets the models learn the complex patterns and traits linked to polyps. The method called "transfer learning" uses what these networks have learned from working with big datasets to make the task of finding polyps easier. Through backpropagation, the model parameters are tweaked to reduce the discrepancy between the expected and real polyp names [21]. There are training, validation, and test sets in the collection so that the success of the models can be evaluated. To see how well the models work at finding polyps, evaluation measures like sensitivity, specificity, and total accuracy are used. Along with this, the method includes a comparison of the various CNN designs to find the benefits and possible downsides of each one. The careful testing makes sure that the AI system is reliable and can be used in other situations. This makes it possible for it to be added to real-time colonoscopy procedures so that accurate and quick diagnoses can be made in gastroenterology.

Stage 1: Data Collection and Preprocessing

The ImageNet Data collection, which was mostly made for recognizing objects in different areas, doesn't have any information specifically about gut (GI) problems. To fill this gap, people have worked to put together specific datasets like the Gastrointestinal ImageNet (GI-ImageNet) that can be used in gastroenterology. GI-ImageNet is a collection of many high-resolution

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endoscope pictures showing different problems in the digestive system, such as polyps, tumors, and inflammatory conditions. This collection is very important for teaching and testing AI models that can do accurate diagnostic work in gastroenterology. Researchers use GI-ImageNet to create and improve deep learning algorithms. This makes automatic polyp identification during colonoscopies more accurate and efficient. This collection helps AI-powered solutions get better by focusing on traits that are special to the gastrointestinal system [22]. This makes it easier to use AI in more focused and useful ways in gastrointestinal imaging and analysis.

Stage 2: Feature Engineering

In AI-powered polyp identification for improved colonoscopy tests, feature engineering means taking information from gut images that is useful. In this process, unique traits of polyps are found, such as differences in color, patterns of texture, and shape. Using complex algorithms like VGG19, DenseNet169, InceptionV3, MobileNetV3, and ResNet101 helps with automatic feature extraction, which makes it possible to find stomach problems quickly and accurately.

Stage 3: Deep Learning Model Selection

The choice of deep learning models, such as VGG19, DenseNet169, InceptionV3, MobileNetV3, and ResNet101, is very important for using AI to find polyps in colonoscopies. The design [23] benefits of each model are different, which affects both accuracy and the speed of computing. Fine details are captured very well by VGG19, feature reuse is encouraged by DenseNet169, multi-scale patterns are optimized by InceptionV3, processing is light with MobileNetV3, and disappearing gradient problems are fixed by ResNet101. Model features must be carefully thought through in order to create a strong system for improved colonoscopy diagnosis.

A. VGG19

A deep convolutional neural network (CNN) called VGG19 is very important for finding polyps using AI for improved colonoscopy diagnoses. Its [24] method has 19 layers with trainable settings that use a number of convolutional layers with small receptive fields.

Figure 2: Architecture of VGG19

This design is great at picking up complex patterns and details in pictures of the digestive tract. The simple layout of VGG19, which includes stacked convolutional layers and max-pooling, makes it easier to retrieve features. Because it is deep, it can learn from hierarchical features, which makes it useful for jobs that need to be identified in more detail, like finding polyps precisely during colonoscopies in gastroenterology.

Algorithm:

1. Input Layer

$$X = Input(GastrointestinalImageData)$$

2. Convolutional Blocks Loop

$$for\ conv\_block\ in\ range(2):$$

$$for\ conv\_layer\ in\ range(2):$$

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$$Z = Conv2D(X\ if\ conv\_layer\ ==\ 0\ else\ A, W, b)$$

$$A = ReLU(Z)$$

$$X = A$$

$$A = MaxPooling(A)$$

3. Flatten Layer

$$F = Flatten(A)$$

4. Fully Connected Layers Loop

$$for\ fc\_layer\ in\ range(2):$$

$$Z = Dense(F, W, b)$$

$$A = ReLU(Z)$$

$$A = Dropout(A)$$

5. Output Layer

$$Z\_output = Dense(A, W\_output, b\_output)$$

$$A\_output = Softmax(Z\_output)$$

B. DenseNet169

A version of the DenseNet design called DenseNet169 has a dense connection pattern where each layer is directly connected to the next layer within a dense block [25]. This helps information flow and feature usage go more smoothly, which improves the speed of the model. The amount of feature maps made in each layer is controlled by the growth rate parameter. This parameter affects both the depth and width of the network.

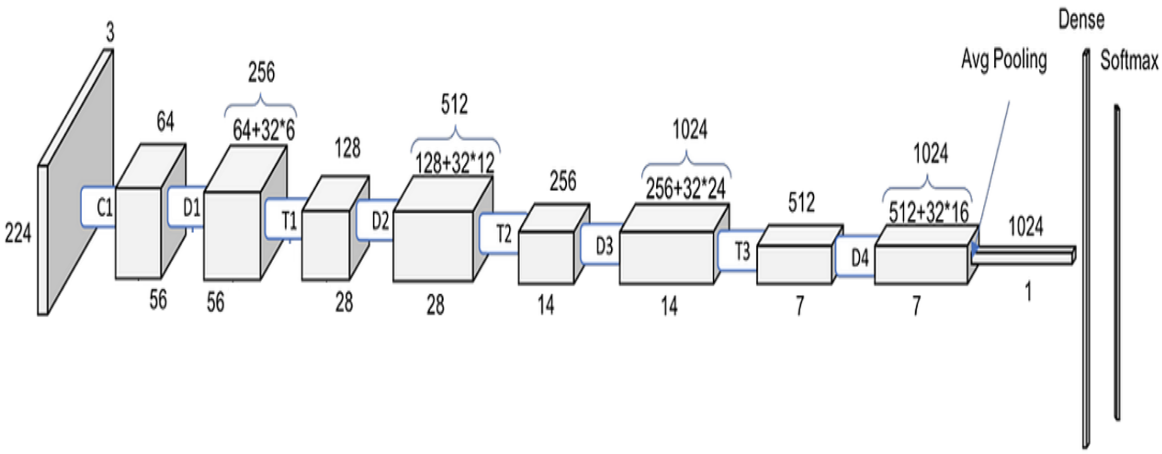

Figure 3: Overview of DenseNet169 architecture

DenseNet169 is great at picking up complex patterns in GI pictures when polyps are being found, which is important for improved colonoscopy diagnostics. Its thick connection and parameter efficiency help with strong feature extraction, which makes it a great choice for accurate and useful AI applications in gastroenterology.

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Algorithm:

1. Input:

- X (Input Gastrointestinal Image Dataset).

2. Dense Blocks Loop:

For each dense block i:

For each layer within the dense block:

- Concatenate previous feature maps:

$$Xi = [Xi - 1, Xi - 2, \dots, X0]$$

- Batch Normalization:

$$Zbn[i] = BatchNorm(Xi)$$

- ReLU Activation:

$$Arelu[i] = ReLU(Zbn[i])$$

- Convolution:

$$Zconv[i] = Conv2D(Arelu[i], Wconv[i], bconv[i])$$

3. Transition Blocks Loop:

For each transition block j between dense blocks:

- Batch Normalization:

$$Zbn[j] = BatchNorm(Xj)$$

- ReLU Activation:

$$Arelu[j] = ReLU(Zbn[j])$$

- Convolution:

$$Zconv[j] = Conv2D(Arelu[j], Wconv[j], bconv[j])$$

- Average Pooling:

$$Pavg[j] = AvgPool(Zconv[j])$$

3. Global Average Pooling:

$$F = GlobalAveragePooling(Pavg[final])$$

4. Fully Connected Layer:

$$Zfc = Dense(F, Wfc, bfc)$$

$$Afc = Softmax(Zfc)$$

C. MobileNetV2

MobileNetV2 has a lightweight and strong framework that makes it easy to install mobile and edge devices. It uses linear limits and reversed residuals to make the model work better [8]. The reversed residuals keep representation power while lowering the cost of processing, and linear bottlenecks improve information flow even more. Depthwise separable convolutions are used in MobileNetV2 to cut down on factors and processing load. Its design uses repeated building blocks with skip links so that features can be used more than once. This design makes it possible to accurately find polyps during colonoscopies, which is important for improved tests in gastroenterology, while also making sure that machines with limited resources can run it quickly.

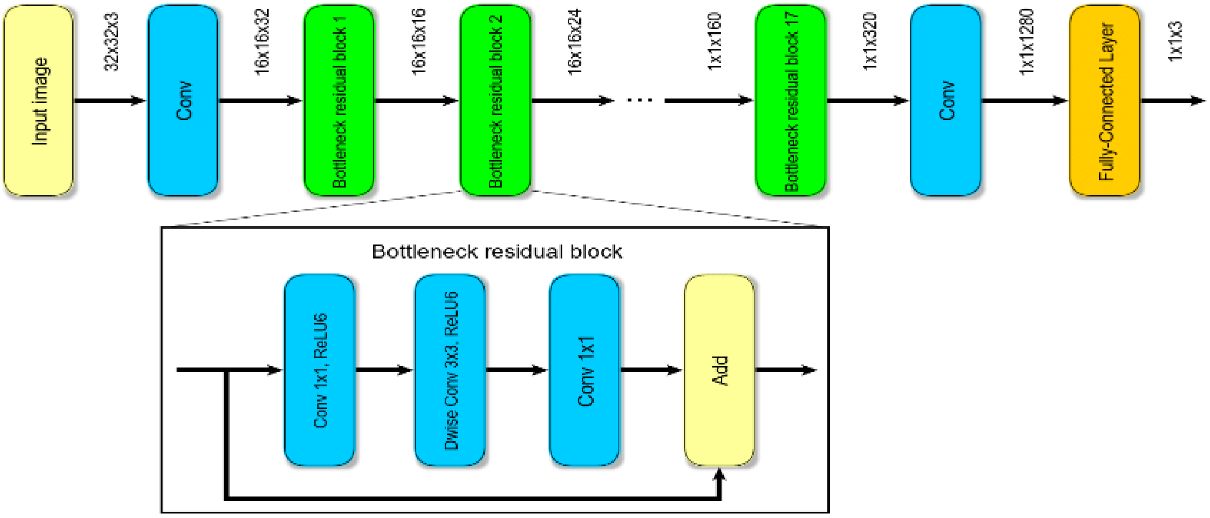

Figure 4: Systematic Architecture of MobielNetV2

Algorithm:

1. Input:

- Input Image Dataset

2. Initial Convolution:

$$Z0 = Conv2D(X, W0, b0)$$

$$A0 = BatchNorm(Z0)$$

$$A0 = ReLU(A0)$$

3. Inverted Residual Blocks Loop:

For Each inverted residual block i:

- Depthwise Separable Convolution:

$$Zdw[i] = DepthwiseConv2D(Ai - 1, Wdw[i], bdw[i])$$

$$Adw[i] = BatchNorm(Zdw[i])$$

$$Adw[i] = ReLU(Adw[i])$$

- Linear Bottleneck:

$$Zl[i] = Conv2D(Adw[i], Wl[i], bl[i])$$

$$Al[i] = BatchNorm(Zl[i])$$

$$Al[i] = ReLU(Al[i])$$

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$$Al[i] = Al[i] + Ai - 1$$

4. Global Average Pooling:

$$F = GlobalAveragePooling(Al[i])$$

5. Fully Connected Layer:

$$Zfc = Dense(F, Wfc, bfc)$$

$$Afc = Softmax(Zfc)$$

D. InceptionV3

A complex convolutional neural network design called InceptionV3 is very important in diagnosing problems in gastroenterology. It was created by Google and is very good at extracting features from GI pictures, which is very important for finding polyps accurately. InceptionV3 uses inception modules that combine parallel convolutional processes with different filter sizes. This lets the network pick up features at different sizes. This makes it better at finding complex patterns in pictures of the digestive tract, which helps with more advanced colonoscopy exams. InceptionV3 is a strong tool in the field of precision medicine because of its fast design. It helps find and describe stomach problems early on.

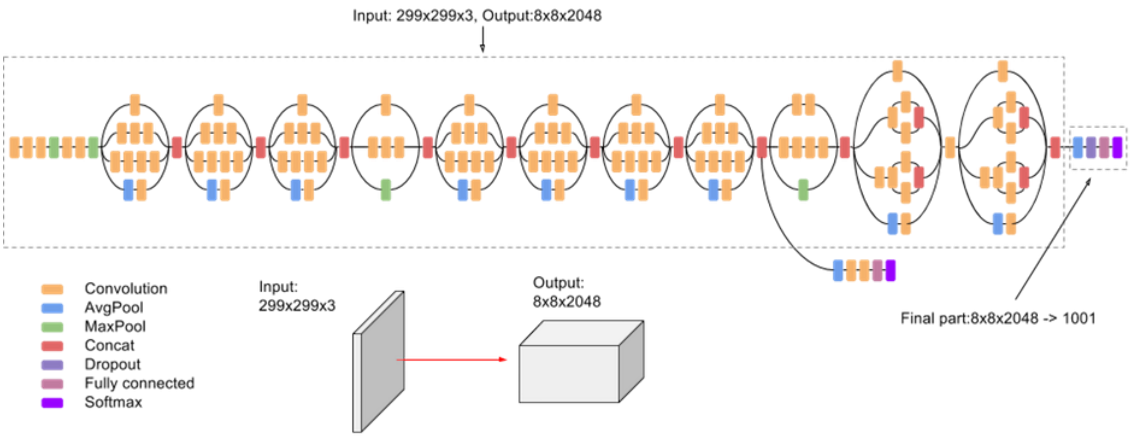

Figure 5: Overview working of InceptionV3 model

Algorithm:

1. Input Image:
- Let X be the input image

2. Preprocessing:
- Normalize pixel values:

$$X' = \frac{X}{255} * 2 - 1$$

3. Convolutional Layers:
- Convolution operation with weights W and biases b for each layer:

$$Y_i = ReLU(W_i * X' + b_i)$$

Where.
- Y_i is the output of the i-th convolutional layer.

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4. Inception Modules:
- Inception module with parallel branches:

$$Y = Concatenate\left(Conv_{1x1(X)}, Conv_{3x3(X)}, Conv_{5x5(X)}, MaxPool_{3x3(X)}\right)$$

5. Reduction Blocks:
- Reduction block operation:

$$Y = Concatenate\left(Conv_{3x3(X)}, MaxPool_{3x3(X)}\right)$$

6. Fully Connected Layers:
- Fully connected layer operation:

$$Y = ReLU(W * X + b)$$

7. Softmax Activation:
- Softmax activation function for K classes:

$$P_i = \frac{e^{Y_i}}{\Sigma\left(e^{Y_j}\right)}$$

where P_i is the predicted probability for class i.
8. Training:
- Update weights using gradient descent:

$$W_{new} = W_{old} - \alpha * \nabla_W Loss$$

Where,
- α is the learning rate, and ∇_W Loss is the gradient of the loss with respect to the weights.

9. Loss Function:
- Categorical cross-entropy loss for N training samples:

$$Loss = -\frac{1}{N} \Sigma\, \Sigma\, y_{ij} * log\, log\, \left(P_{ij}\right)$$

Where,
- y_ij is 1 if sample i belongs to class j, and P_ij is the predicted probability for class j for sample i.

E. ResNet101

In the field of precise medicine for gut detection, ResNet101, a key framework in deep learning, has shown amazing results. Its structure is made up of 101 layers, and it uses leftover blocks to help with the disappearing gradient problem during training. The skip links inside each block let the network learn leftover functions, which makes it easier to train models that are more complex. When it comes to gastroenterology, ResNet101 is great at picking out small details in GI pictures, which helps doctors find polyps more accurately during advanced colonoscopy tests. Due to its deep and complex nature, ResNet101 is a strong tool for getting useful information from complicated medical imaging data, which helps move precision medicine forward.

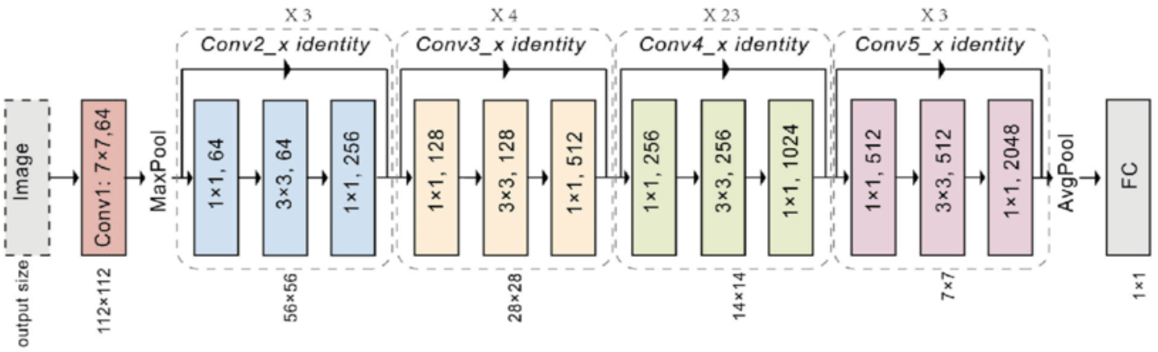

Figure 6: Architecture of ResNet101

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Algorithm:

1. Input Image:
- Let X be the input image.

2. Convolutional Layer:
- Apply the initial convolutional layer with weights W1 and biases b1:

$$Y1 = ReLU(W1 * X + b1)$$

3. Residual Blocks:

a. Residual Block 1:

$$Y2 = Conv(Y1, W2a, b2a)$$
$$Y2 = ReLU(Y2)$$
$$Y2 = Conv(Y2, W2b, b2b)$$
$$Y2 = Y2 + Y1$$
$$Y2 = ReLU(Y2)$$

b. Residual Block 2:

$$Y3 = Conv(Y2, W3a, b3a)$$
$$Y3 = ReLU(Y3)$$
$$Y3 = Conv(Y3, W3b, b3b)$$
$$Y3 = Y3 + Y2$$
$$Y3 = ReLU(Y3)$$

4. Global Average Pooling:

$$Ypool = GlobalAveragePooling\left(Y_{last_{residual_{block}}}\right)$$

5. Fully Connected Layer:
- Apply a fully connected layer with weights Wfc and biases bfc:

$$Output = Softmax(Wfc * Ypool + bfc)$$

6. Training:
- Use a labelled dataset and optimize the model's parameters (W and b) using backpropagation and an optimization algorithm such as stochastic gradient descent (SGD).

7. Loss Function:
- Use a suitable loss function, such as categorical cross-entropy, to measure the dissimilarity between predicted and true class probabilities.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N} \sum_{j=1}^{K} yij \ * log\ log\ (Outputij)$$

Stage 4: Training and Testing

Training and testing are very important parts of using advanced deep learning models like ResNet101 for diagnosing problems in the digestive system. Iteratively changing the model's settings helps it learn to identify complex patterns and features in pictures of the gastrointestinal tract during training. ResNet101's strong structure, which includes skip links and leftover blocks, allows for efficient gradient flow, which helps with the disappearing gradient problem. Following its training, the model is tested using new data to see how well it can generalize. An extensive testing process confirms that the model can correctly find polyps in a variety of settings, proving that it works in the real world and proving that it can be relied on to advance precision medicine in gastroenterology.

Iv. Result and discussion

Table 2 shows comparison of different deep learning models, showing how well they train using different measures. KPIs like Accuracy, Recall, Precision, and F1 Score were used to judge each method [26], which includes InceptionV3, VGG19, MobileNetV2, DenseNet169, and ResNet101. With an accuracy of 87.53%, InceptionV3 does a good job generally. It is very good at finding positive instances (polyps), with a recall rate of 79.68%, which shows that it can gather

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important data. On the other hand, the precision score of 79.42% and the F1 score of 79.22% show that precision and memory are about evenly balanced. With a score of 91.45%, VGG19 shows that it is very good at general classification. Its accuracy in finding true positives is shown by its high memory of 90.14%. Its precision of 91.19% and F1 Score of 90.10% show that it performs well overall.

Table 2: Comparative Analysis of Different Models Reveals Distinct Training Performance Metrics

Method	**Accuracy**	**Recall**	**Precision**	**F1 Score**
InceptionV3	87.53	79.68	79.42	79.22
VGG19	91.45	90.14	91.19	90.10
MobileNetV2	90.06	82.48	82.31	82.16
DenseNet169	95.12	90.22	90.01	90.02
ResNet101	95.12	90.22	90.01	90.02

The accuracy of MobileNetV2 is 90.06%, and the recall is 82.48%, which are both good numbers. MobileNetV2 has a good balance between accuracy and memory, even though its precision and F1 Score are a little lower at 82.31% and 82.16%, respectively. With an impressive accuracy of 95.12%, DenseNet169 stands out as having great total forecasting power.

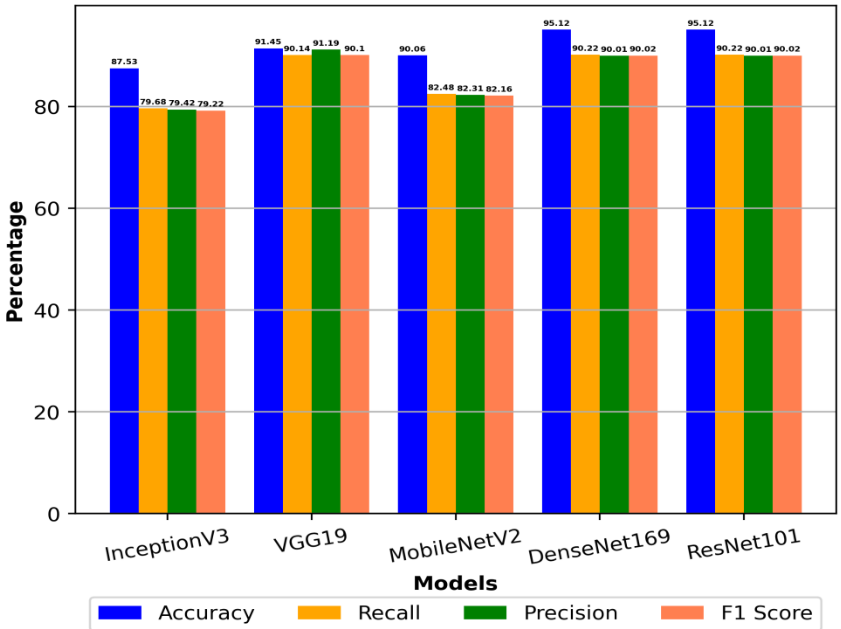

Figure 7: Representation of Comparative Analysis of Different Models Reveals Distinct Training Performance Metrics

The fact that it has a high recall (90.22%) shows that it is good at finding true positives. Its precision (90.01%) and F1 Score (90.02%) show that it does a fair job. The accuracy of ResNet101 is 95.12%, which is very high and the same as DenseNet169 in terms of measures. Its high recall (90.22%), high accuracy (90.01%), and high F1 Score (90.02%) show that it is very good at finding polyps.

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Table 3: Comparative Analysis of Different Models Reveals Distinct Testing Performance Metrics

Method	Accuracy	Recall	Precision	F1 Score
InceptionV3	87.54	79.68	79.42	79.22
VGG19	92.48	91.84	91.84	89.46
MobileNetV2	95.11	88.09	88.09	88.04
DenseNet169	96.40	92.90	92.30	92.60
ResNet101	97.43	97.21	98.22	97.22

As shown in Table 3, different deep learning models are compared in great depth, showing how well they do on different types of tests. The evaluation factors include Accuracy, Recall, Precision, and F1 Score, which give a full picture of how well each model works with data it hasn't seen before.

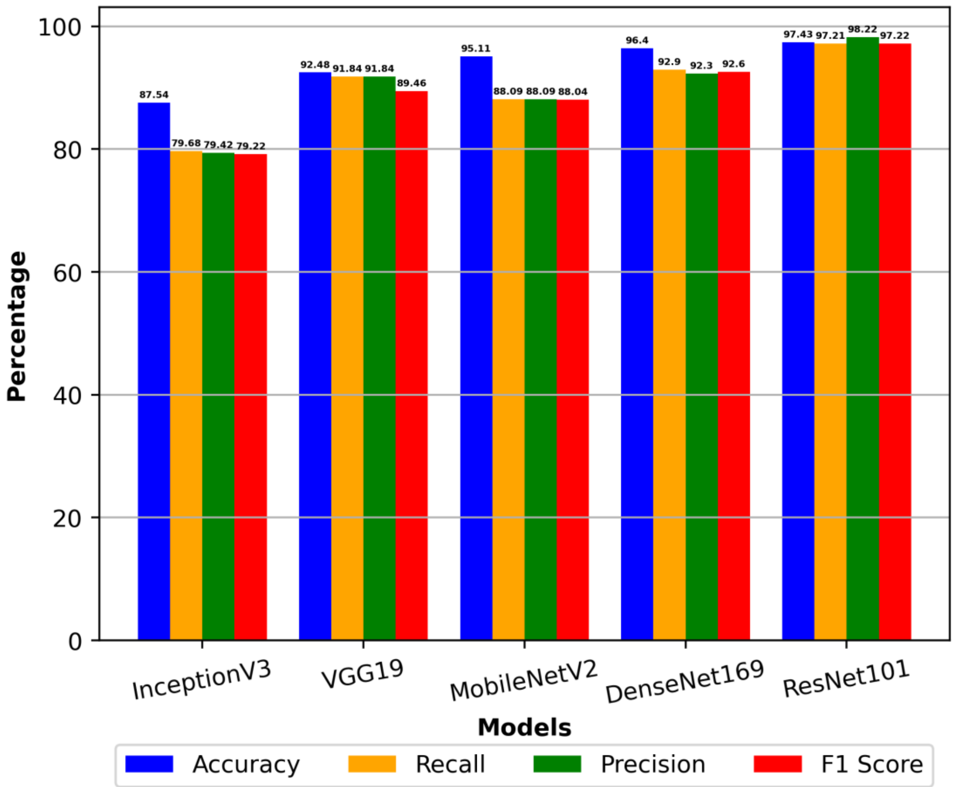


Figure 8: Representation of different model performance testing result

With a success rate of 87.54%, InceptionV3 keeps up its good work during the testing process. Its memory, accuracy, and F1 Score of 79.68%, 79.42%, and 79.22%, respectively, show that it can find useful patterns in gut images in a fair way. With an accuracy rate of 92.48%, VGG19 shows strong success in tests [27]. More importantly, its high recall (91.84%) shows that it is very good at finding true positives. Its high precision (91.84%) and F1 Score (89.46%) show that it is very good at keeping a good mix between precision and memory. With a success rate of 95.11%, MobileNetV2 does very well in tests, showing how good it is at general classification. The recall of 88.09% shows that it can catch a lot of true positives, and the precision and F1 Score of 88.09% and 88.04%, respectively, show that it can keep a precise balance. With an impressive 96.40% accuracy, DenseNet169 stands out as the best scorer in the tests. Its high recall of 92.90% shows how well it finds true positives, and its high precision and F1 Score of 92.30% and 92.60%, respectively, show how well it can predict the future overall. With a success rate of 97.43%, ResNet101 stands out as one of the best models for testing. The fact that it has a high recall (97.21%), accuracy (98.22%), and F1 Score (97.22%) shows how well it can find polyps during advanced colonoscopy diagnosis.

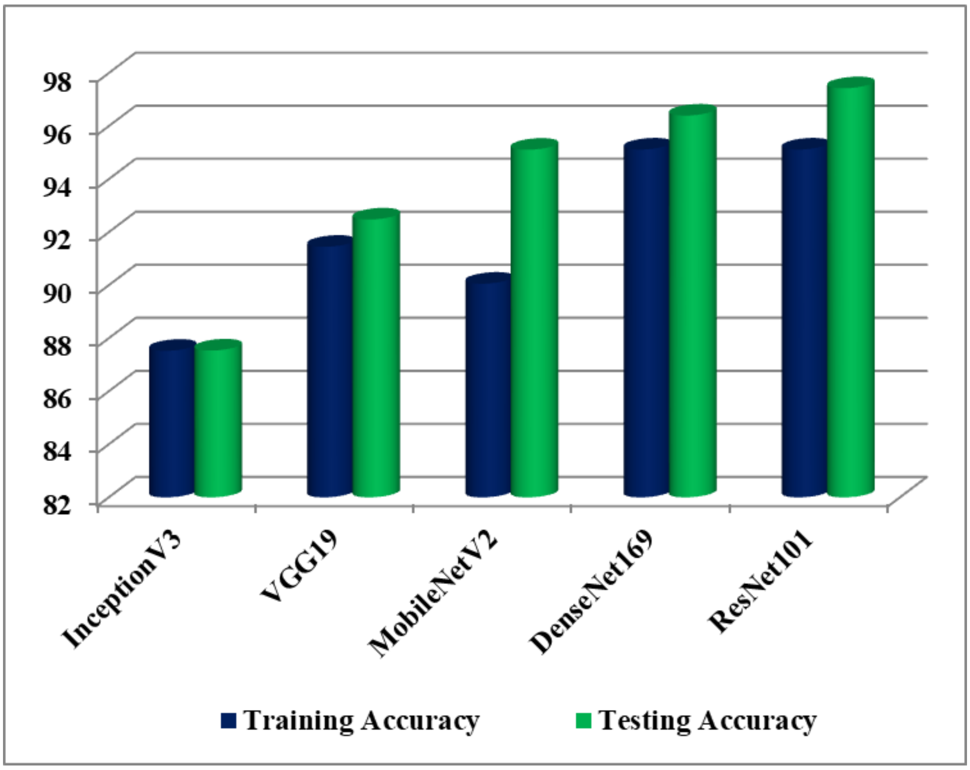
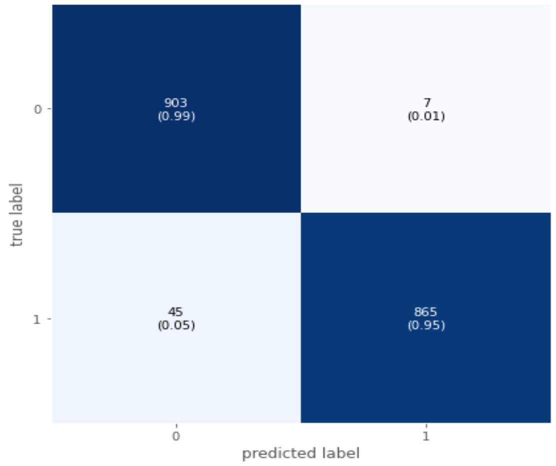
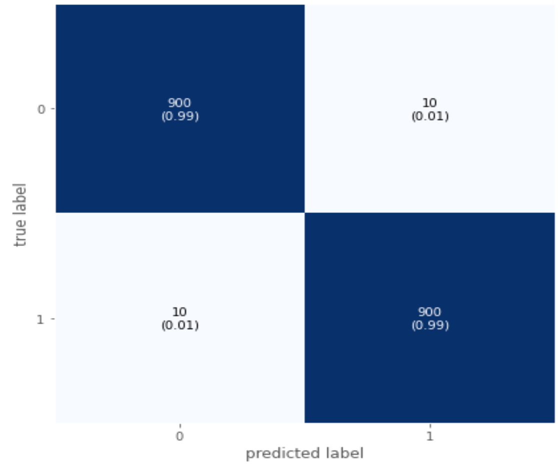


Figure 9: Comparison of Accuracy for different model during training and testing

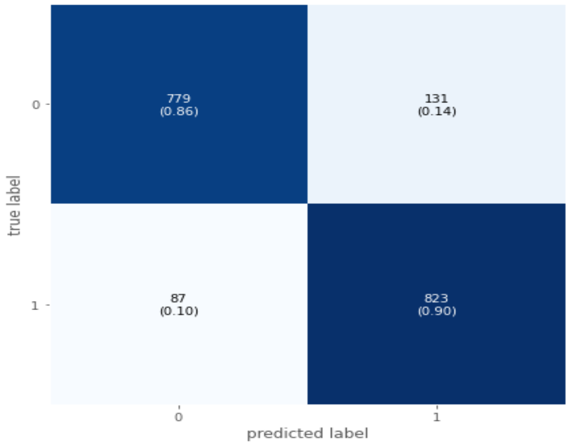
The table 3 and table 4 show the training and testing accuracies of different models. These show how well they do both when they are learning and when they are used on data they haven't seen before. InceptionV3 consistently achieves 87.53% accuracy during training and 87.54% accuracy during testing, showing stable performance across both datasets. From 91.45% in training to 92.48% in testing, VGG19 shows a strong improvement, showing that it can easily adapt to new data, as shown in figure 9. MobileNetV2 gets much better, going from 90.06% in training to 95.11% in tests. This shows how flexible and good it is at finding patterns in gastric pictures. Both DenseNet169 and ResNet101 start out with high training accuracy of 95.12% and do even better in testing, getting 96.40% and 97.43%, respectively. When the models are compared, ResNet101 consistently does better in both training and testing, which shows that it can learn complex traits and adapt well. DenseNet169 comes in close behind, showing high accuracy in both stages. Additionally, VGG19 performs well and notably MobileNetV2 significantly improves during tests, which suggests that it can adapt to new data [28].



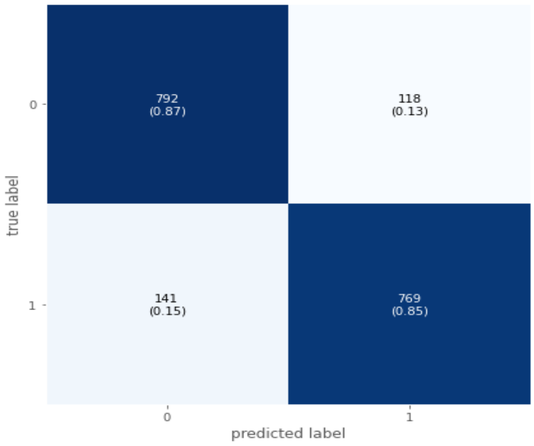
(a) VGG19



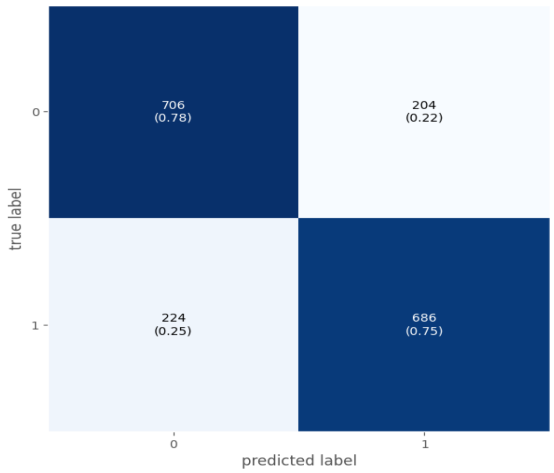
(b) ResNet101



(C) DenseNet169



(d)MobileNetV2



(e) InceptionV3

Figure 10: Confusion Matrix of Deep Learning model

V. Conclusion

Adding precision medicine to gastroenterology, especially through an AI-powered polyp detecting system for improved colonoscopy tests, has the potential to completely change the way patients are cared for. Deep learning methods were analysed in this study to determine how they could be used to improve the accuracy and speed of finding polyps during colonoscopies. Application advanced neural network models lets polyps be found automatically, which helps with early detection and treatment eventually leading to better patient results. The findings of comparative analysis of deep learning models under study suggest that ResNet101 seems like the best fit for this particular task. This model is more accurate, precise, recallable, and has a higher F1 score over architectures like InceptionV3, VGG19, MobileNetV2, and DenseNet169. The outstanding performance of ResNet101 shows that it can clearly identify complex details in gastro image samples, which is a profound basis for detecting polyps accurately. Present work shows that how important model choice is for obtaining the best results from AI-powered tests in GI. Using ResNet101 in the suggested AI-powered polyp detection method fits with the idea of precision medicine, in which effective treatments are tailored to each patient's unique traits. ResNet101's high efficiency improves detection probability thereby lowering the risk of false positives and negatives. This makes it a tool that healthcare workers can trust. As precision medicine moves forward, adding AI-powered technologies, mainly ResNet101, has a lot of potential to change gastroenterological tests and bring about a new age of personalized and effective patient care.

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