International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 09 | Sept – 2025 DOI: 10.55041/ISJEM05039
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Colorectal Cancer Detection Using Deep and Transfer Learning

G.VIJAYA LAKSHMI, M.RENUKA DURGA,

[1]Assistant Professor,[2]Student,

[1]Computer Science and Engineering[2]MTech Final Semester,

[2]Department of Computer Science and Engineering

[1]Sanketika Vidya Parishad Engineering College, Vishakhapatnam, Andhra Pradesh, India

ABSTRACT:
Early correct diagnosis of Colorectal cancer stands as the fundamental factor to boost patient survival because this cancer ranks as a global leader both in incidence and mortality rates. The standard colonoscopy with biopsy tests work well in diagnosis yet they severely impact patient comfort through their extensive nature and variable observational results. The recent developments in artificial intelligence particularly deep learning enabled precise automated interpretation of medical images through advances made in recent years. A study researches the identification of colorectal cancer in histopathological images while using Xception and MaxVit networks with transfer learning. The architectures were chosen considering their established strengths the depthwise separable convolutions of Xception that facilitate efficiency and the hybrid vision transformer architecture of MaxViT that captures local and global image dependencies. 1,51,118 histopathological images from a dataset were classified into Microsatellite Stable (MSS) and Microsatellite Instability-Mutated (MSIMUT) classes for training, validation, and testing. The system demonstrated strong performance in model classification after pre-training its versions while reducing expenses and accelerating training duration. The proposed approach strengthens pathologic assessments through reliable outcomes and stable performance while introducing scalability to help clinicians with diagnosis processes for CRC in an expedient manner.
IndexTerms -Colorectal Cancer (CRC), Deep Learning, Transfer Learning, Histopathology /Histopathological Images, Microsatellite Stable (MSS), Microsatellite Instability-Mutated (MSIMUT), Xception Model.

1.INTRODUCTION

The project is in the interdisciplinary field of Medical Imaging and Artificial Intelligence with an emphasis on the use of state-of-the-art Deep Learning techniques to enhance early detection of Colorectal Cancer (CRC) . Over the past few years, the intersection of available large-scale medical imaging datasets and computationally exponential growth has allowed deep learning models to dominate the identification of subtle features and anomalies in medical scans—details that frequently escape human observation.[14] This paradigm shift in diagnosis promises much in the fight against one of the most lethal and most diagnosed cancers globally.Colorectal cancer has a huge global health impact, being the third most common cancer and the second leading cause of cancer death worldwide. According to the statistics from the World Health Organization (WHO), an estimated 1.9 million new cases of CRC and 9,35,000 deaths are reported each year . The American Cancer Society emphasizes the lifetime risk of developing CRC is approximately 1 in 23 among men and 1 in 25 among women, emphasizing the prevalence of the disease.[7] As much as it is prevalent, early-stage CRC is usually asymptomatic or nonspecific in nature, resulting in delayed diagnosis and treatment. Yet, when diagnosed in its early stages, CRC is very treatable, with survival rates of over 90%, and thus early detection is essential for better outcomes. The conventional diagnostic methods like colonoscopies, tissue biopsies, and visual examination of the histopathological slides by pathologists are commonly practiced but are intrinsically invasive, time-consuming, and resource-intensive. In addition, human analysis is prone to human error in the case of large quantities of intricate images or when image structure and clarity are inconsistent. The manual process also involves a heavy cognitive and temporal burden on healthcare providers, emphasizing to the imperative for automated systems that can complement diagnostic precision and efficiency .[10]

1.1 Existing System

Colorectal cancer is currently diagnosed using colonoscopy, biopsy, and histopathological examination, which are invasive, time-consuming, and costly. Pathologists face difficulties due to large volumes of images and subtle differences between healthy and cancerous tissues, often leading to human error and inconsistent results. Traditional machine learning methods depend on handcrafted features, which are insufficient for complex tissue patterns, and many existing models suffer from data imbalance, overfitting, and poor generalization. High computational needs further limit their use in resource-constrained settings. These drawbacks highlight the need for an AI-based automated system to improve accuracy, speed, and reliability in cancer detection.[8]

1.1.1 Challenges:

- Conventional methods like colonoscopy and biopsy are invasive, costly, and uncomfortable for patients.
- Manual analysis of histopathological images is time-consuming and labor-intensive.
- Diagnosis is prone to human error, fatigue, and inter-observer variability.
- Traditional machine learning models rely on handcrafted features, which fail to capture complex tissue structures.
- Limited availability of annotated datasets reduces training efficiency.
- Class imbalance in medical data often leads to biased predictions.[11]

1.2 Proposed system:

The proposed system introduces an AI-based automated framework for colorectal cancer detection using advanced deep learning and transfer learning techniques. It leverages Convolutional Neural Networks (CNNs) and pre-trained models such as Xception and MaxViT to classify histopathological images into Microsatellite Stable (MSS) and Microsatellite Instability-Mutated (MSIMUT) categories.[9] By employing transfer learning, the system reduces training time, minimizes overfitting, and achieves high accuracy even with limited annotated medical data.

The models automatically extract both local and global image features, eliminating the need for handcrafted features and improving diagnostic precision. Data augmentation techniques further enhance robustness and generalization. With its scalable design, the proposed system ensures faster, reliable, and reproducible cancer detection while reducing dependency on manual interpretation. Ultimately, this framework aims to support pathologists by providing accurate second-opinion results, improving early diagnosis, and enabling integration into real-world clinical workflows.[4]

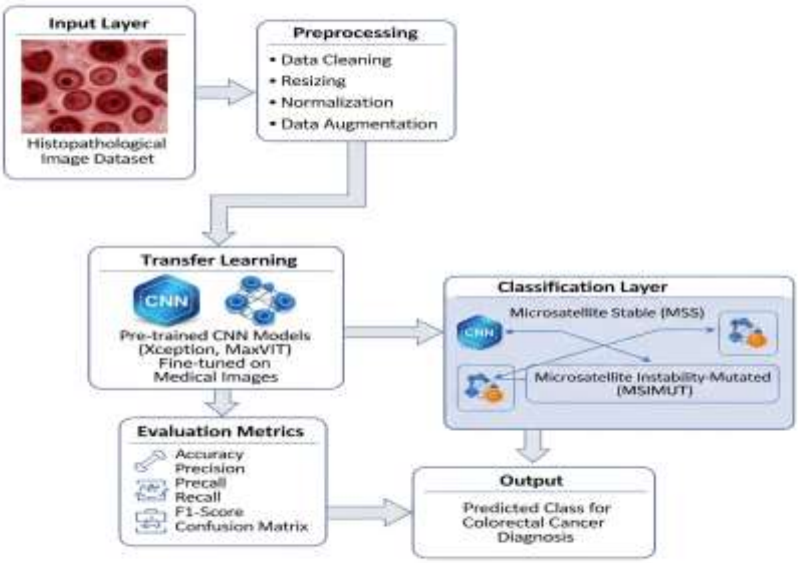

Fig: 1 Proposed Diagram

1.2.1 Advantages:

- **Non-invasive and automated** – Reduces patient discomfort compared to colonoscopy and biopsy-based methods.[2]
- **High accuracy** – Deep learning models (Xception, MaxViT) improve classification performance for MSS and MSIMUT.
- **Time-efficient** – Faster diagnosis compared to manual examination of histopathological slides.
- **Minimizes human error** – Provides consistent and objective predictions, reducing observer variability.
- **Utilizes transfer learning** – Leverages pre-trained CNN models to achieve high performance even with limited medical datasets.
- **Captures complex patterns** – Automatically extracts both local and global features from images without handcrafted features.[5]
- **Scalable and reproducible** – Can handle large datasets and produce uniform results across different scenarios.

2 LITERATURE REVIEW:

Sara Hosseinzadeh Kassani, Peyman Hosseinzadeh Kassani and Michal J. Wesolowski compare deep transfer learning-based models for colorectal cancer histopathology segmentation. The research analyzes the suitability of deep transfer learning technology for histopathological image segmentation in colorectal cancer early diagnosis? The research used challenging histology data comprised of colorectal tissue specimens with distinctive shapes and uneven textures through whole slide images (WSIs). The research explored many deep learning models through convolutional neural networks (CNNs) including DenseNet and LinkNet designed for encoder-decoder segmentation operations. The models obtained efficiency through pre-training methods together with patch-wise fine-tuning procedures for processing large WSI datasets. When tested in combination the shared DenseNet-LinkNet proved to be the most effective architecture.The experimental portion shows that transfer learning technique enables better segmentation accuracy while requiring less training time. The system demonstrates reliable functionality together with consistent performance for medical facility operation. The research analysis provides significant information that helps select optimal encoder backbones for segmentation tasks in medical image processing.

2.1 Architecture:

The architecture of the proposed system is designed to classify histopathological images of colorectal cancer into Microsatellite Stable (MSS) and Microsatellite Instability-Mutated (MSIMUT) classes using deep learning and transfer learning.[13]

1. **Input Layer**: The system takes a large dataset of 151,118 histopathological images categorized into MSS and MSIMUT.
2. **Preprocessing**: Images undergo cleaning, resizing, normalization, and data augmentation to enhance quality, balance classes, and reduce overfitting.
3. **Feature Extraction**: Three advanced deep learning architectures are employed:
   - **Xception** – uses depthwise separable convolutions for efficiency and accuracy.[15]
   - **MaxViT** – combines CNN and transformer mechanisms to capture both local and global dependencies.[1]
4. **Transfer Learning**: Pre-trained models (trained on large datasets like ImageNet) are fine-tuned on medical images, reducing training time and improving accuracy with limited annotated data.
5. **Classification Layer**: The extracted features are processed through dense layers with activation functions (Softmax/Sigmoid) to classify images into MSS or MSIMUT.
6. **Evaluation Metrics**: The system's performance is assessed using Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.
7. **Output**: The final output provides the predicted cancer class (MSS or MSIMUT) along with reliable decision support for pathologists, enabling faster and more consistent diagnosis.[12]

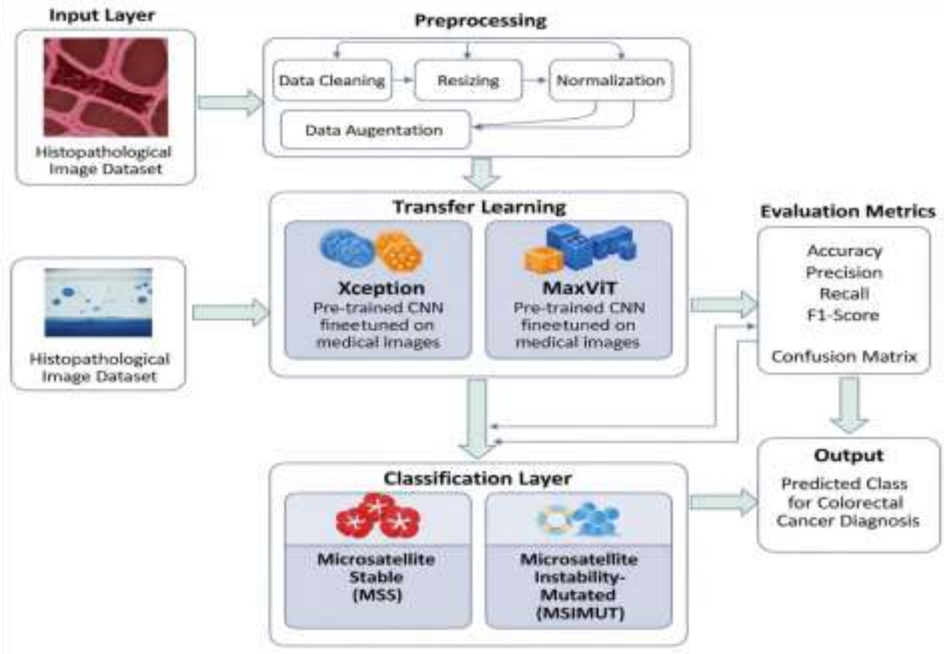

Fig:2 Architecture

2.2 Algorithm

- **Xception**
- Based on *depthwise separable convolutions* for efficiency and accuracy.
- Uses ReLU activation (hidden layers), Softmax (output), and Adam optimizer.
- Total: 126 layers.[3]
- **MaxViT (Maximally Attentive Vision Transformer)**
- Hybrid of CNN + Transformer.
- Uses multi-axis attention (window + grid attention) to capture both local and global features.
- Includes MBConv blocks, Layer Normalization, GELU activation, Adam optimizer.
- 11 layers (core transformer blocks[6]

2.2 Techniques:

- **Deep Learning with Convolutional Neural Networks (CNNs)**
- CNNs were employed to automatically extract spatial and morphological features from histopathology images without manual feature engineering.
- They helped capture subtle differences between normal and cancerous tissues.
- **Transfer Learning**
- Pre-trained models (trained on large datasets like ImageNet) were fine-tuned on colorectal cancer histopathology images.
- This reduced training time, prevented overfitting, and improved generalization on a limited medical dataset.
- **Data Augmentation**
- Techniques such as scaling, flipping, and adding noise were used to artificially increase dataset variability.
- This improved robustness of the models and helped prevent overfitting.
- **Advanced Architectures**
- **Xception**: Uses depthwise separable convolutions for efficiency and high accuracy.
- **MaxViT (Vision Transformer)**: Combines CNN-like local feature extraction with transformer-based global attention.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 09 | Sept – 2025 DOI: 10.55041/ISJEM05039
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

- **Hyperparameter Tuning**
- Careful optimization of learning rate, batch size, dropout rate, activation functions (ReLU, Softmax, SiLU, GELU), and optimizers (Adam, RMSprop).
- Early stopping and ReduceLROnPlateau were used to avoid overfitting and optimize training.
- **Evaluation Techniques**
- Performance measured using **Confusion Matrix**, **Accuracy, Precision, Recall, F1-score**.
- Comparative study and ablation study were done to identify the best-performing model (Xception).

2.3 Tools:

SOFTWARE TOOLS:

- **Python 3.x** – Main programming language.
- **TensorFlow / Keras** – Deep learning frameworks used to build and train CNN and transfer learning models (Xception, MaxViT).
- **OpenCV** – Image preprocessing and handling histopathology images.
- **NumPy / Pandas** – Numerical computations and dataset handling.
- **Matplotlib / Seaborn** – Visualization of graphs, accuracy plots, and confusion matrices.
- **Google Colab / Jupyter Notebook** – Development and execution environment for coding, model training, and testing.

HARDWARE TOOLS:

- **GPU-enabled system** – For faster deep learning training.
- **Minimum 8GB RAM** – To handle large medical image datasets.
- **SSD Storage** – For quick data loading and efficient dataset handling.

2.4 Methods:

- **Data Collection & Preparation** – A dataset of 1,51,118 histopathology images (MSS and MSIMUT) was used, split into 70% training, 20% validation, and 10% testing for balanced evaluation.
- **Data Augmentation** – Techniques like scaling, flipping, and noise addition were applied to improve dataset diversity and prevent overfitting.
- **Transfer Learning** – Pre-trained ImageNet models were fine-tuned for colorectal cancer classification, reducing training time and improving accuracy.
- **Deep Learning Models** – Three architectures were implemented: Xception (efficient convolutions) and MaxViT (CNN + Transformer hybrid).
- **Hyperparameter Optimization** – Learning rate, batch size, dropout, and activation functions were tuned, with EarlyStopping and ReduceLROnPlateau used to prevent overfitting.
- **Model Evaluation** – Models were assessed using Accuracy, Precision, Recall, F1-score, and confusion matrices, with Xception giving the best overall performance.

3. METHODOLOGY

3.1 Input:

The input to the project consisted of histopathology images of colorectal cancer, with a total of 1,51,118 samples divided into two categories: Microsatellite Stable (MSS) and Microsatellite Instability-Mutated (MSIMUT). These high-resolution images captured tissue structures and cellular morphology, serving as the raw data for training, validation, and testing of deep learning models to classify colorectal cancer. The dataset was balanced across both classes, ensuring fairness in model learning. Images were preprocessed and resized to standard dimensions to fit the model requirements. This large dataset provided a strong foundation for building accurate and reliable deep learning-based classification models.

3.2 Method of Process:

The process of this project begins with collecting and preprocessing histopathology images of colorectal cancer, followed by data augmentation to increase variability and prevent overfitting. Next, transfer learning is applied by fine-tuning pre-trained models (Xception and MaxViT) on the dataset. The models are trained using optimized hyperparameters such as learning rate, batch size, and dropout, with techniques like EarlyStopping

ISSN: 2583-6129
DOI: 10.55041/ISJEM05039

and ReduceLROnPlateau to ensure efficient convergence. Finally, the trained models are evaluated using Accuracy, Precision, Recall, F1-score, and confusion matrices**,** and a comparative study is conducted, where Xception achieved the best performance among all models.

3.3 Output:

The output of the project is **a** trained deep learning model capable of accurately classifying colorectal histopathology images into two categories: Microsatellite Stable (MSS) and Microsatellite Instability-Mutated (MSIMUT)**.** The models produced evaluation results in the form of accuracy, precision, recall, F1-score, and confusion matrices, which helped measure their effectiveness. Among the tested architectures, Xception achieved the best performance with an accuracy of 90.00%**,** making it the most reliable model for colorectal cancer detection. The project thus delivers an automated system that supports early diagnosis and assists pathologists in medical decision-making.

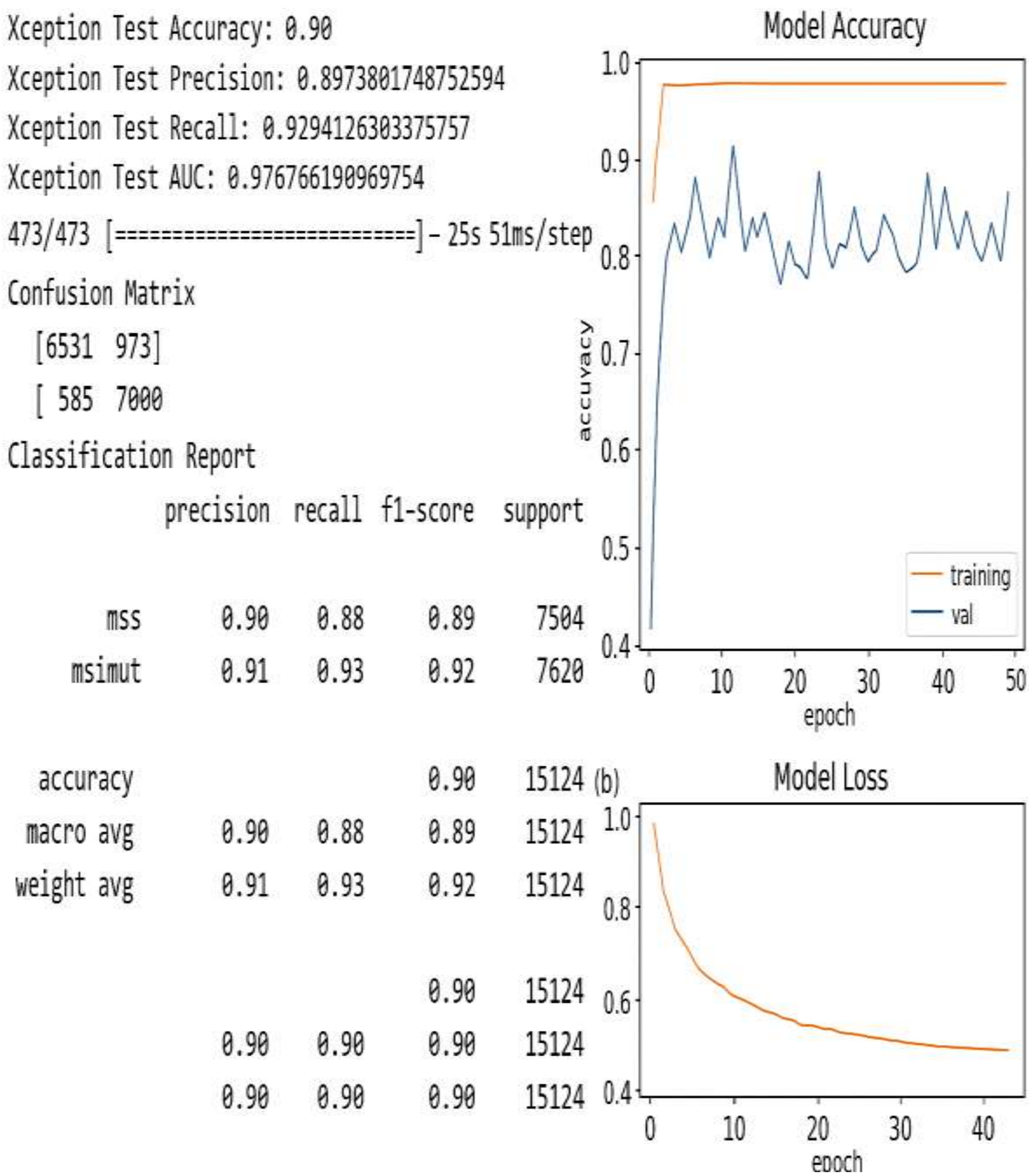

Fig: Xception Training vs Validation Accuracy and Loss

ISSN: 2583-6129
DOI: 10.55041/ISJEM05039

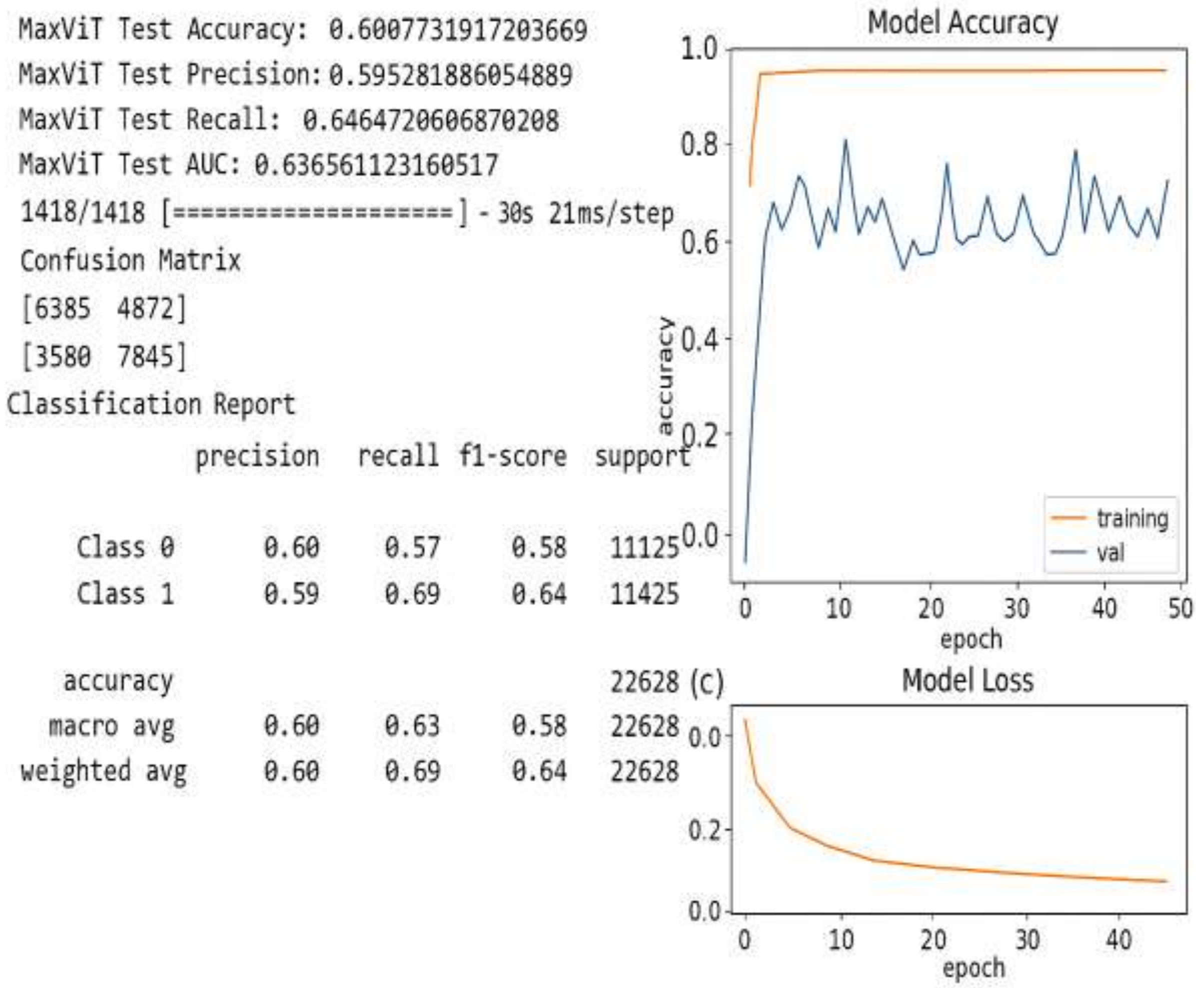

Fig: MaxVit Training vs Validation Accuracy and Loss

4.RESULTS:

The project demonstrated that deep learning with transfer learning can effectively detect colorectal cancer from histopathological images with high accuracy. Among the tested models, Xception achieved the best performance with 90.00% accuracy, 89.73% precision, 92.94% recall, and a 89% F1-score, making it the most reliable model for classification. MaxViT lagged behind with only 60.07% accuracy. Overall, the results confirm that the proposed system, especially using the Xception model, can provide accurate and dependable support for early and automated colorectal cancer diagnosis.

5. DISCUSSIONS:

The project discusses how deep learning and transfer learning significantly improve the accuracy and efficiency of colorectal cancer detection from histopathological images. It highlights that Xception outperformed MaxViT, achieving the highest accuracy, precision, recall, and F1-score, making it the most balanced model. The results also emphasize the value of transfer learning in handling limited medical datasets, reducing training time, and preventing overfitting. Additionally, the project discusses challenges such as intra-class variability of tissue, limited annotated data, and the need for real-time diagnostic support. By comparing with other models like VGG16, ResNet50, and MobileNetV2, the study reinforces that Xception provides the most dependable performance. Overall, the discussion underlines the potential of AI-powered systems to assist pathologists, reduce human error, and provide scalable, reliable, and faster colorectal cancer diagnosis in clinical practice.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 09 | Sept – 2025 DOI: 10.55041/ISJEM05039
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

6. CONCLUSION:

This project demonstrates the effective use of deep learning and transfer learning for automating colorectal cancer classification from histopathological images. Using a dataset of over 150,000 images, two models—Xception and MaxViT—were trained to distinguish between MSS and MSIMUT categories. The models achieved high accuracy, with Xception performing best, showing the potential of CNNs to extract complex patterns and improve diagnostic precision. Transfer learning further enhanced performance by reducing computational needs and reliance on large annotated datasets. The study also addressed challenges such as intra-class variability, limited data, and the need for real-time support, ultimately presenting a scalable and reliable framework for computer-aided cancer diagnostics.

7. FUTURE SCOPE:

The future scope of this project offers several promising directions. One important area is improving model generalization across diverse datasets, ensuring robustness when applied to different hospitals, demographics, and imaging scanners. Another key direction lies in integrating AI systems with clinical workflows by building user-friendly interfaces and adhering to regulatory standards such as HIPAA and FDA guidelines. Enhancing explainability and trust in AI is also crucial, where techniques from Explainable AI (XAI) can help clinicians interpret predictions with confidence. Additionally, the system can be extended to multi-class and multi-modal analysis, going beyond MSS vs. MSIMUT classification to include genomic data, clinical notes, or other imaging modalities. Optimizing models for edge deployment and real-time processing would allow usage in low-resource or portable medical settings, increasing accessibility. Finally, incorporating continuous learning approaches, such as incremental or active learning, would enable the models to evolve and improve as new medical data becomes available, ensuring long-term adaptability and reliability.

8.ACKNOWLEDGEMENT:

Mrs.G. Vijaya Lakshmi, M.Tech (Ph.d) working as an Assistant Professor and Head of the Department in the Department of Computer Science and Engineering, Sanketika Vidya Parishad Engineering College, affiliated by Andhra University and approved by AICTE, Visakhapatnam, AP with 5 years teaching experience and member of IAENG, accredited by NAAC with her areas of interests in C, Data Warehousing and Data Mining, Design and Analysis of Algorithms, Python, Formal Languages and Automata Theory, Compiler Design.

Mandadhi.Renuka Durga is pursuing her final semester M.Tech (CST) in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Deep Learning and Transfer Learning. M Naga Keerthi has taken up her PG project on COLORECTAL CANCER DETECTION USING DEEP AND TRANSFER LEARNING and published the paper in connection to the project under the guidance of Mrs.G.Vijaya Lakshmi, Assistant Professor, Head of the Department in the Department of Computer Science and Engineering, SVPEC.

.

REFERENCES

[1] A systematic study of transfer learning for colorectal cancer detection

https://www.sciencedirect.com/science/article/pii/S2352914823001387

[2] A novel transfer learning approach for the classification of histological images of colorectal cancer

https://link.springer.com/article/10.1007/s11227-020-03575-6

[3] Deep transfer learning based model for colorectal cancer histopathology segmentation: A comparative study of deep pre-trained models

https://www.sciencedirect.com/science/article/abs/pii/S1386505621002951

[4] Deep transfer learning methods for colon cancer classification in confocal laser microscopy images

https://link.springer.com/article/10.1007/S11548-019-02004-1

[5] Automatic Detection of Colorectal Polyps Using Transfer Learning
https://www.mdpi.com/1424-8220/21/17/5704

[6] Transfer learning based approach for lung and colon cancer detection using local binary pattern features and explainable artificial intelligence (AI) techniques
https://peerj.com/articles/cs-1996/

[7] Transfer Learning Approach and Nucleus Segmentation with MedCLNet Colon Cancer Database
https://link.springer.com/article/10.1007/s10278-022-00701-z

[8] Galactic swarm optimization with deep transfer learning driven colorectal cancer classification for image guided intervention
https://www.sciencedirect.com/science/article/abs/pii/S0045790622006772

[9] Computer-Assisted Diagnosis of Lymph Node Metastases in Colorectal Cancers Using Transfer Learning With an Ensemble Model
https://www.sciencedirect.com/science/article/pii/S0893395223000236

[10] Advanced Raman Spectroscopy Based on Transfer Learning by Using a Convolutional Neural Network for Personalized Colorectal Cancer Diagnosis
https://www.mdpi.com/2673-3269/4/2/22

[11] Deep Learning Models for Poorly Differentiated Colorectal Adenocarcinoma Classification in Whole Slide Images Using Transfer Learning
https://www.mdpi.com/2075-4418/11/11/2074

[12] Transfer Learning of Pre- Trained Inception-V3 Model for Colorectal Cancer Lymph Node Metastasis Classification
https://ieeexplore.ieee.org/abstract/document/8484405

[13] Enhancing Colorectal Cancer Histological Image Classification Using Transfer Learning and ResNet50 CNN Model
https://ieeexplore.ieee.org/abstract/document/10218590

[14] Classification of Colorectal Cancer Polyps via Transfer Learning and Vision-Based Tactile Sensing.
https://ieeexplore.ieee.org/abstract/document/9967308

[15] Transfer Learning Fusion Approaches for Colorectal Cancer Histopathological Image Analysis

https://www.mdpi.com/2313-433X/11/7/210