BREAST CANCER DETECTION WITH COMPUTER VISION

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PROBLEM STATEMENT

- Imagine being a doctor staring at a microscopic image, trying to decide if a patient has cancer. It’s time-consuming, subjective, and even experts can disagree.

What if AI could help?

- Instead of a black-box prediction, how does it sound if we build a model that not only classifies cancer but also shows how it made the decision thereby helping doctors trust and understand AI’s role in diagnosis.

MOTIVATION

- We were curious about how AI "***sees***" cancer and wanted to visualize what features it focuses on.

  → Utilize explainability techniques to decode AI’s decision-making process

- We applied: **LIME** for ML models to highlight important regions and **Integrated Gradients** for DL models to track pixel-level influence.
- This allowed us to connect AI predictions with human understanding, making cancer detection more transparent and trustworthy.

ABOUT DATASET

What is BreakHis?

- The Breast Cancer Histopathological Database (BreakHis) is a publicly available dataset containing microscopic images of breast cancer tissue.
- It was collected from 82 patients at 4 different magnification levels.

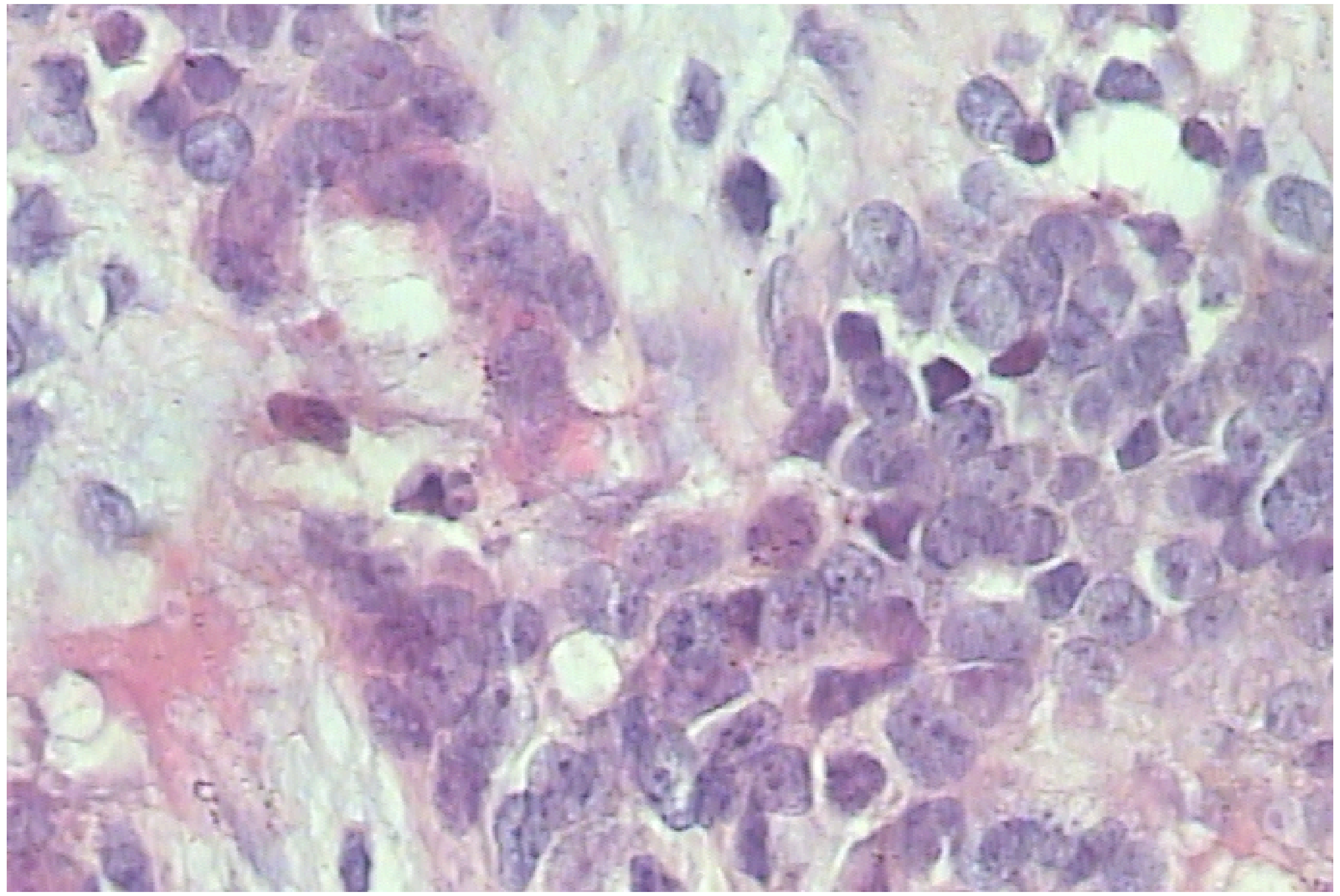
Data Structure

- **Total Images:** 7,909
- **Magnifications:**40x (low zoom), 100x, 200x and 400x (high zoom)
- **Class Labels:** Benign (Non-Cancerous) Tumor and Malignant (Cancerous) Tumor

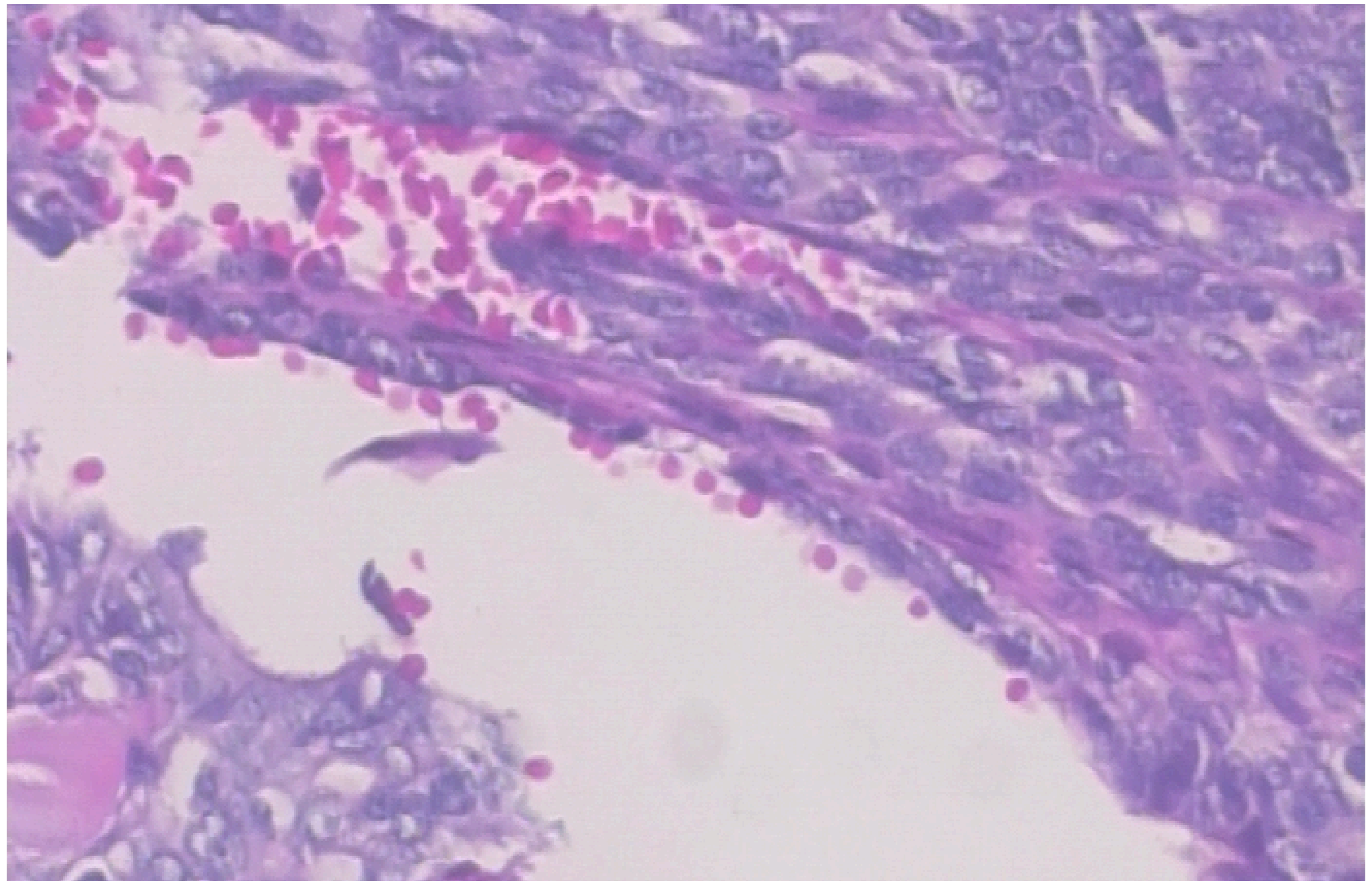
Data Distribution:

- The dataset is imbalanced—malignant samples outnumber benign ones.
- This required us to apply data balancing (undersampling) to ensure fair model training.

Benign



Malignant



Review of Previous Efforts

BreakHis Dataset in Research

- The BreakHis dataset has been widely used for breast cancer classification using histopathological images.
- Traditional approaches have relied on feature extraction methods such as HOG (Histogram of Oriented Gradients) and GLCM (Gray Level Co-occurrence Matrix) combined with Machine Learning classifiers like SVM and Random Forest.

Advances in Deep Learning for Breast Cancer Detection

- **CNN-Based Models:** Convolutional Neural Networks (ResNet, VGG, EfficientNet) have shown significant improvements in accuracy by learning complex patterns directly from images.
- **End-to-End Learning:** Unlike ML models that require feature extraction, CNNs automatically learn hierarchical representations from raw data

Gaps in Existing Work

- **Lack of Explainability:** Most studies focus on accuracy but lack interpretability, making AI decisions difficult to trust in medical applications.
- **Testing of LBP in Feature Extraction:** While LBP is traditionally used in texture analysis, its effectiveness in breast cancer detection was not well explored.
- **Comparison Between ML & DL:** There is limited work comparing traditional ML models with handcrafted features vs. deep learning models, especially in the context of explainability.
- **Integration of Integrated Gradients (IG):** Many DL-based studies did not explore Integrated Gradients (IG) for explainability, which could provide more meaningful visualizations of how deep models detect cancer.

Our Modelling Approach

Goal: Classify breast cancer (benign vs. malignant) using both ML & DL models with explainability.

Two Parallel Pipelines: Machine Learning (ML) Approach: Feature extraction (LBP) → ML classifiers (SVM, RF, Logistic Regression).

Deep Learning (DL) Approach: EfficientNet + Vision Transformer (ViT)

Explainability Integration: LIME to interpret ML model predictions.

Integrated Gradients (IG) for understanding DL model attention

Comparison to a Mean Approach

Naïve Mean Model using GLCM Threshold

- Simple texture-based classification model using the Gray-Level Co-occurrence Matrix (GLCM).
- It first extracts texture features from grayscale images by computing the GLCM.
- Classifies images based on the mean value of the GLCM matrix using a predefined threshold.

Models Evaluated & Model Selection

Machine Learning Models: 1) SVM (Support Vector Machine) 2) Random Forest 3) Logistic Regression.

Deep Learning Model: EfficientNet + Vision Transformer (ViT) for automated feature learning.

Final Model Selection: Random Forest (Best ML Model) vs. EfficientNet + ViT (DL Model).

Explainability applied to both models to verify predictions.

Data Processing Pipeline

1) Dataset Preprocessing:

- Loaded BreakHis dataset and balancing the classes.
- Converted images to LBP features (for ML) and normalized raw pixels (for DL).

2) Feature Extraction & Model Training:

- ML models (RF, SVM, Logistic Regression) used LBP texture features.
- DL model (EfficientNet + ViT) learned deep hierarchical features.

3) Model Evaluation:

- Used Train-Val-Test splits to measure performance.
- Applied accuracy as the evaluation metric.

4) Explainability & Trust:

- LIME for ML models (visualizing critical regions used by RF).
- Integrated Gradients (IG) for DL (highlighting influential pixels in deep learning).

Local Binary Pattern (LBP)

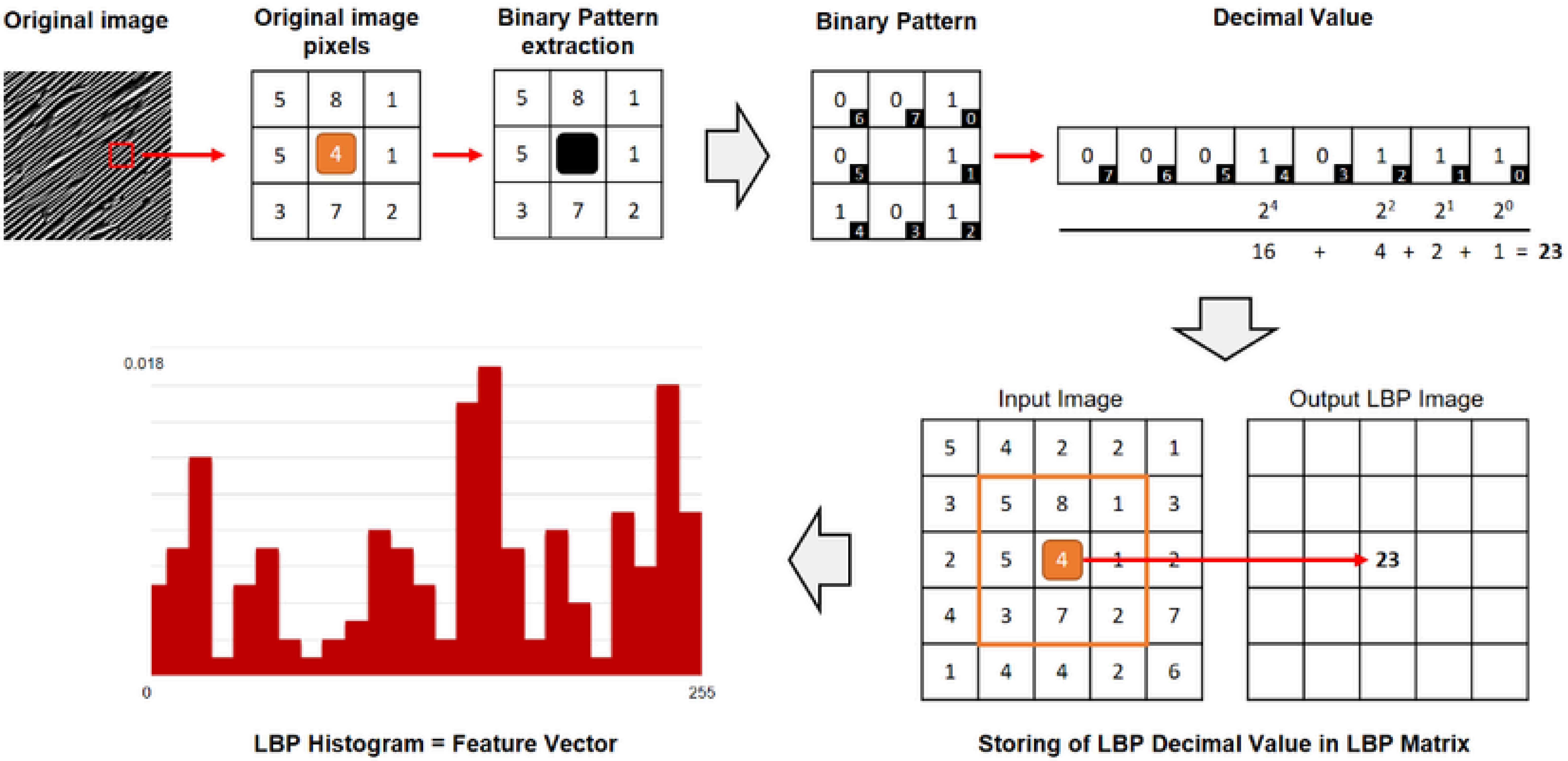


Image Source: https://www.researchgate.net/figure/sualization-of-calculation-of-Local-Binary-Pattern-LBP-An-example-region-of-the_fig1_341341744

Vision Transformer (ViT)

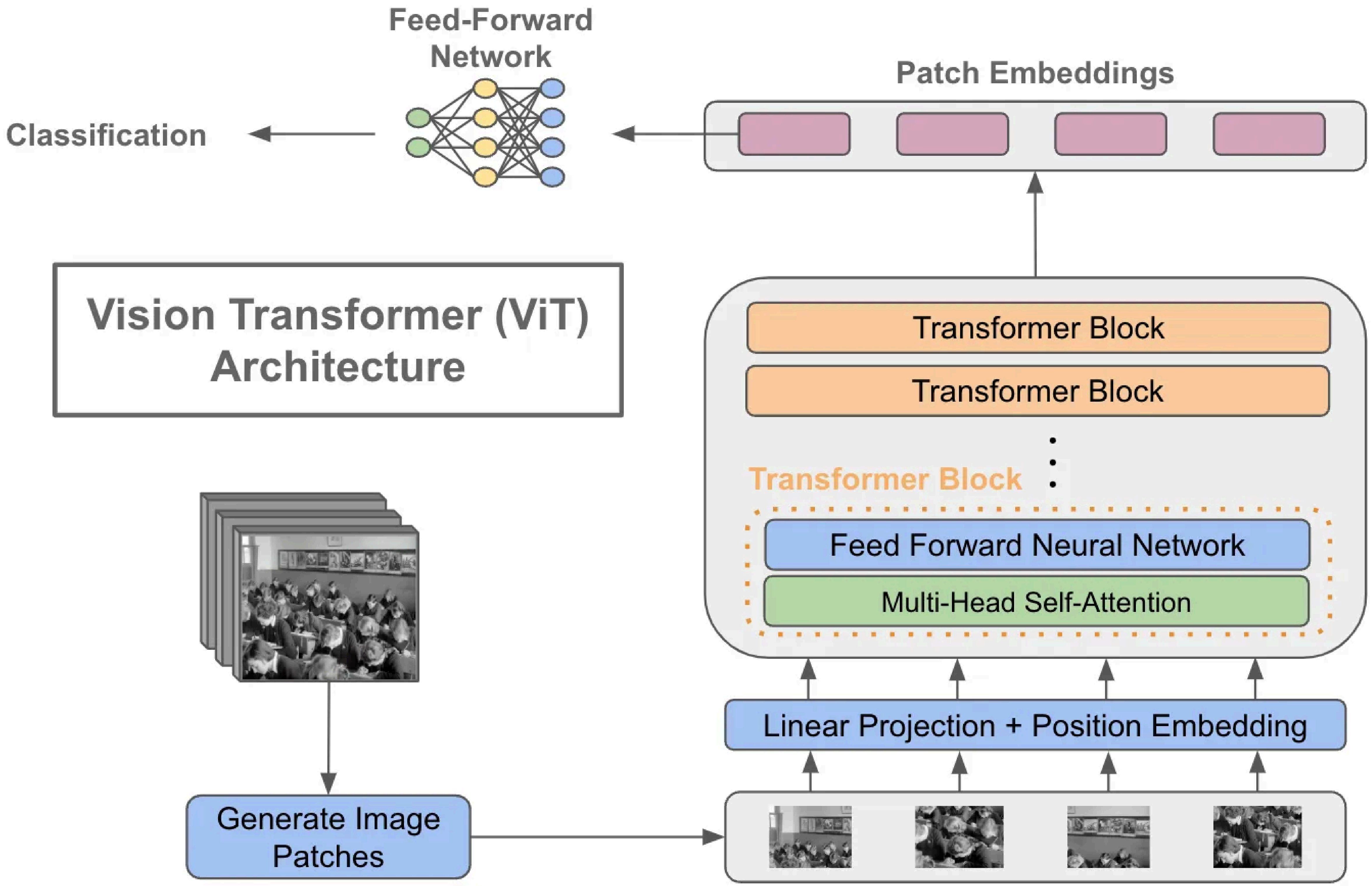


Image Source: https://cameronrwolfe.substack.com/p/vision-transformers

EfficientNet

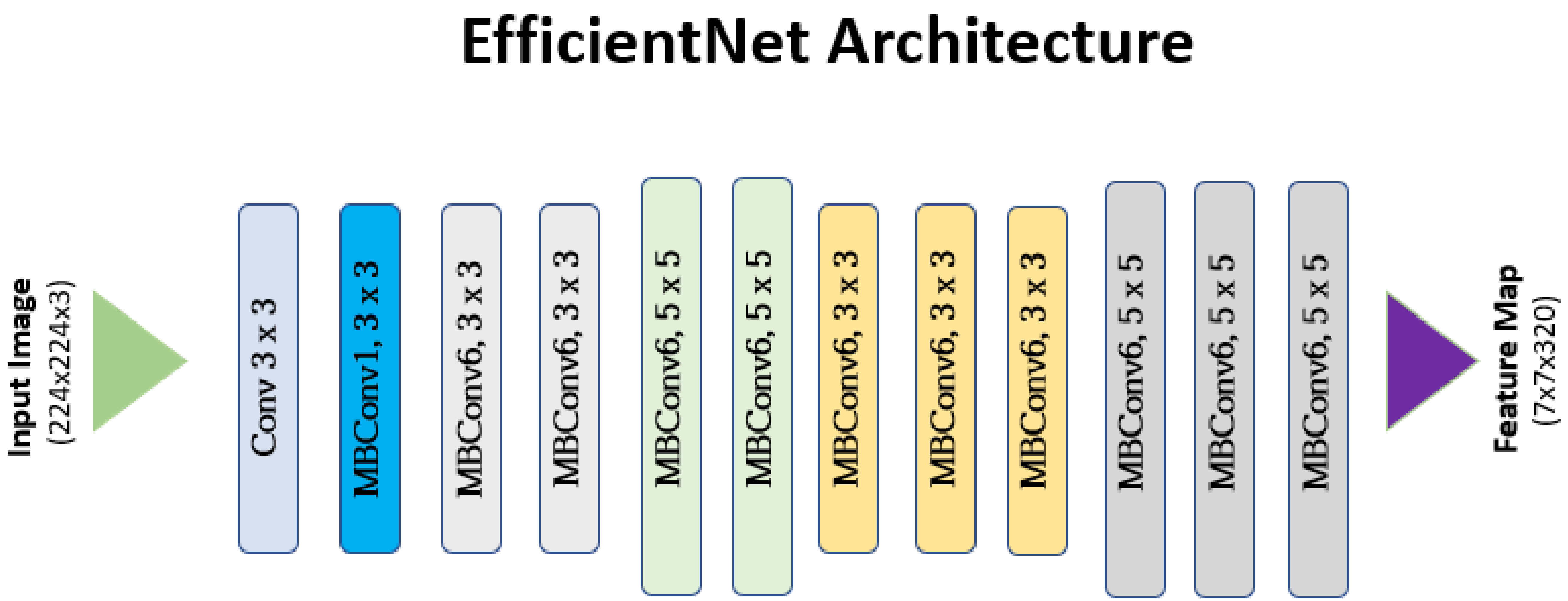


Image Source: https://wisdomml.in/efficientnet-and-its-performance-comparison-with-other-transfer-learning-networks/

EfficientNet + Vision Transformer

Feature Extraction using EfficientNet:

- EfficientNet acts as a CNN backbone to extract low-level and mid-level spatial features.
- The output feature maps are passed to ViT instead of fully connected layers.

Global Context Understanding with ViT

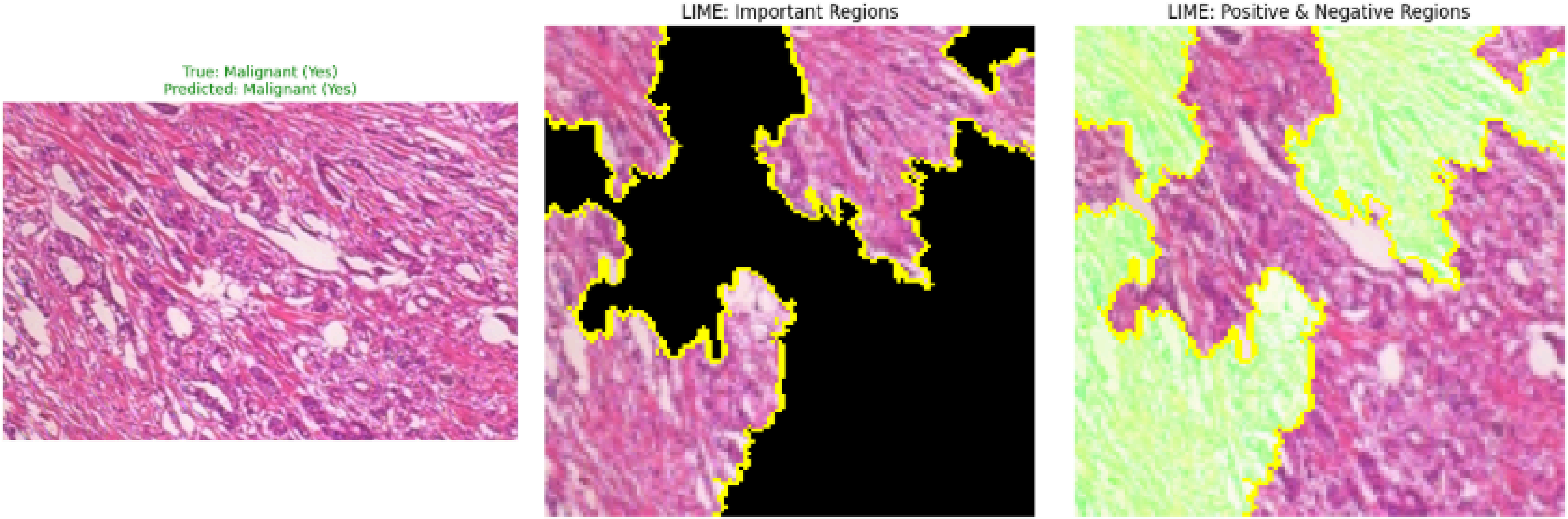
- The extracted feature maps are divided into patches and flattened.
- These patches serve as inputs to the Transformer Encoder, which applies self-attention mechanisms to model long-range dependencies.
- The Transformer captures global relationships and refines the final classification decision.

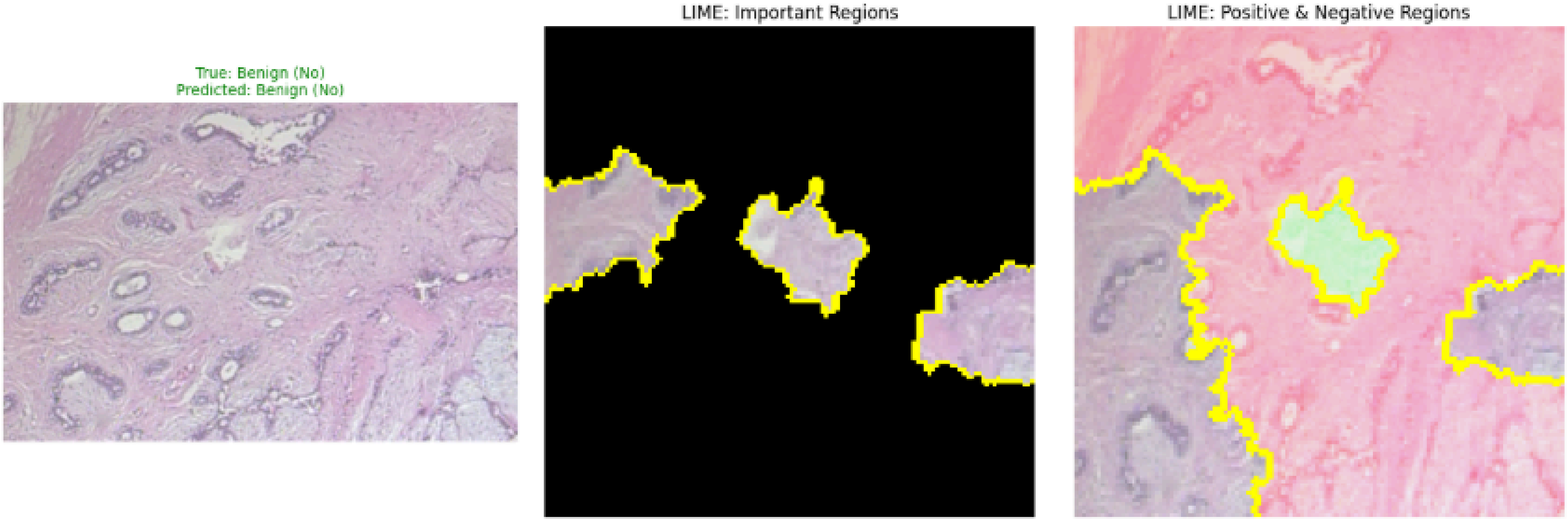
Model Evaluation

Model	Feature Extraction	Accuracy
Random Forest	Local Binary Patterns	87%
Mean Model (Baseline)	Gray Level Co-occurrence Matrix (GLCM)	65%
EfficientNet +ViT	CNN + Transformer Features	92%

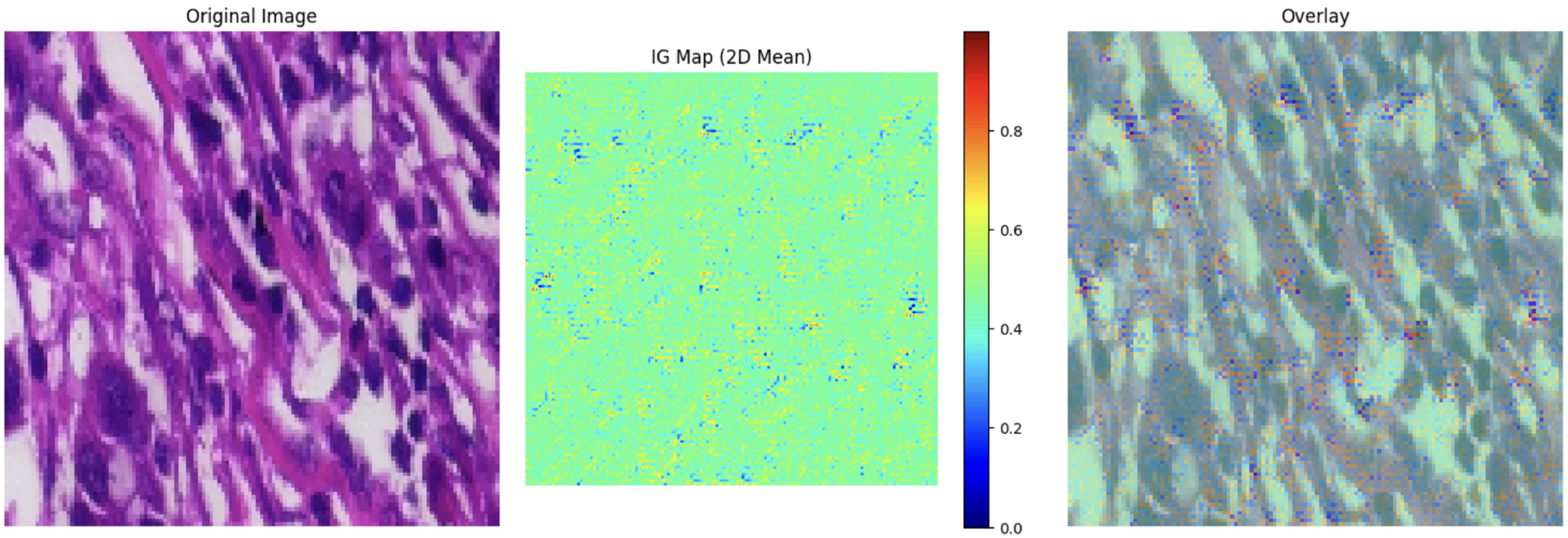
MODEL EXPLAINABILITY

LIME


True: Malignant (Yes)
Predicted: Malignant (Yes)
LIME: Important Regions
LIME: Positive & Negative Regions


True: Benign (No)
Predicted: Benign (No)
LIME: Important Regions
LIME: Positive & Negative Regions

Integrated Gradients



Conclusion

- LBP-based ML models offer a computationally efficient alternative to deep learning.
- Deep learning (ViT) performs slightly better but is more computationally expensive.
- Explainability (LIME & IG) bridges AI and human decision-making, making models trustworthy for real-world use.

Ethics Statement

- **Data Privacy:** We used a publicly available dataset (BreakHis) ensuring no patient data privacy violations.
- **Fairness & Bias:** We applied data balancing techniques to prevent bias toward malignant or benign cases.
- **Interpretability & Trust:** LIME (for ML) & IG (for DL) were used to make AI decisions more transparent for medical use.
- **Clinical Applicability:** While promising, our models should not replace human pathologists but act as decision-support tools.

Final Thought: AI-powered breast cancer detection is not just about accuracy - it is more about making AI transparent, fair, and clinically useful

Thank You!