BREAST CANCER DETECTION

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CONTENT

INTRODUCTION

Breast cancer is the most common cancer worldwide and one of the leading causes of cancer-related deaths. Early and accurate diagnosis plays a huge role in improving survival rates—but today's traditional method, where pathologists manually examine tissue slides, is time-consuming and can be prone to human error.

As the volume of medical data continues to grow, there's a clear need for smarter, faster, and more reliable diagnostic tools.

In our project, we're using a hybrid deep learning approach that combines InceptionV3, Vision Transformers (ViT), and Self-Supervised Learning (SSL). This allows our model to learn both detailed image features and contextual patterns—helping it classify breast cancer subtypes with high accuracy.

The aim is to support pathologists with a tool that improves efficiency, reduces diagnostic errors, and ultimately contributes to better patient care.

MOTIVATION

Breast cancer diagnosis can be the turning point in someone's life. For many patients, catching the disease early means the difference between effective treatment and a late-stage battle. But with the current process relying heavily on manual slide analysis by pathologists, it's easy to see how human limitations—like fatigue or subjective judgment—can affect outcomes.

Furthermore, the volume of histopathological data is increasing rapidly. Pathologists are under increasing pressure to process more cases in less time, raising the risk of missed or delayed diagnoses. This challenge inspired us to explore how technology—especially deep learning—can help.

By combining the power of CNNs like InceptionV3, the attention mechanism of Vision Transformers, and the adaptability of Self-Supervised Learning, we can build a model that not only matches but potentially exceeds human-level performance in some diagnostic tasks.

PROBLEM STATEMENT

- Target Audience: Healthcare professionals (pathologists, oncologists, radiologists).
- Primary Users: Hospitals, clinics, research institutions.
- Functionality: Automates classification of histopathology images.
- Benefits:
    - Reduces workload
    - Improves diagnostic accuracy
    - Speeds up diagnosis
- Additional Users: Medical researchers and students exploring AI in healthcare.
- Policy Impact: Provides data insights for better healthcare resource allocation.
- Overall Goal: Enhance patient outcomes through early detection and treatment of breast cancer.

CONTRIBUTIONS & NOVELTY

- Combines CNNs, ViT, SSL, and Inception V3 for a robust, state-of-the-art AI strategy.
- Inception V3 effectively extracts intricate patterns in histopathology images.
- SSL enables the model to learn from unlabeled data, minimizing the requirement for large annotated datasets.
- ViT extracts global image features that may be overlooked by traditional CNNs.
- Excels at identifying and classifying various breast cancer subtypes.
- Transfer learning with pre-trained ImageNet models enhances accuracy and accelerates development.
- Exceeds many existing tools in reliability, flexibility, and diagnostic assistance.
- Delivers significant innovation to AI in healthcare and early cancer detection.

LITERATURE WORK

CNNs, especially InceptionV3, have been effective in classifying cancer from medical images.

Vision Transformers are newer but great at capturing global image context.

Self-supervised learning helps models learn without large labeled datasets.

SUMMARY

Models usually focus on either local (CNN) or global (ViT) features—not both.

SSL is promising but underused in this domain.

There's progress, but better, more balanced models are needed.

RESEARCH GAP

No strong hybrid model that combines CNN, ViT, and SSL for breast cancer classification.

Limited use of SSL to reduce labeling effort.

A need for models that are both accurate and practical for clinical use

METHADOLOGY

1.Data Preparation & Preprocessing

Begin with collecting histopathology images labeled as Benign or Malignant.
Images are resized, normalized, and augmented using flipping, rotation, and zooming to improve model performance and prevent overfitting.
For the Vision Transformer, images are split into patches to capture fine-grained details.

2. Self-Supervised Learning (SSL)

Since labeling medical images is a time-intensive process, we used Self-Supervised Learning to pretrain our model on unlabeled images.
This approach allowed the model to learn useful visual features early on, helping it perform better when trained on the actual labeled data.
SSL helped us make the most of the data we had and reduced our dependence on manual labeling.

3. Hybrid Deep Learning Model

A hybrid deep learning model combining InceptionV3 and Vision Transformer is used for binary classification. InceptionV3 captures local features like cell shapes and textures, while the Vision Transformer focuses on global patterns across image regions. Their outputs are fused to form a comprehensive feature representation, which is then passed through fully connected layers to classify images as Benign or Malignant.

4. Training & Evaluation

The model was trained using the Binary Cross-Entropy loss function and optimized with the Adam optimizer. We evaluated the model using metrics like Precision, Recall, and F1 Score to ensure balanced and reliable performance across both classes.

APPROACH

Hybrid Deep Learning Architecture

- InceptionV3: Pretrained CNN used for extracting fine-grained local features from histopathology images.
- Vision Transformer (ViT): Captures global spatial relationships by processing image patches using self-attention.
- Self-Supervised Learning (SSL): Used to pretrain the model on unlabeled data to improve feature learning before fine-tuning on labeled data

HARDWARE

- High-performance workstations with robust processors and ample RAM for model training.
- Local storage for model and dataset saves.

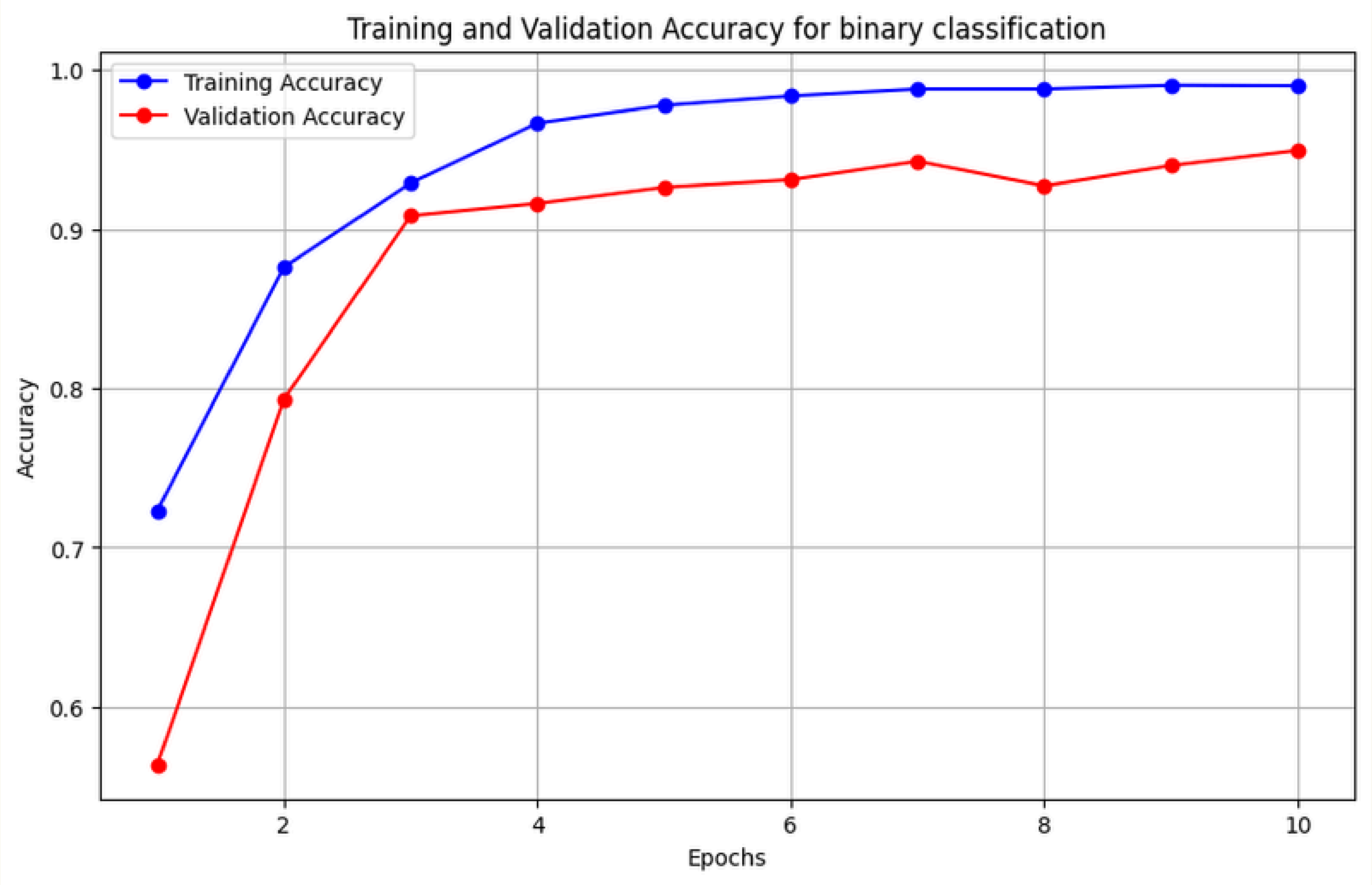
SOFTWARE

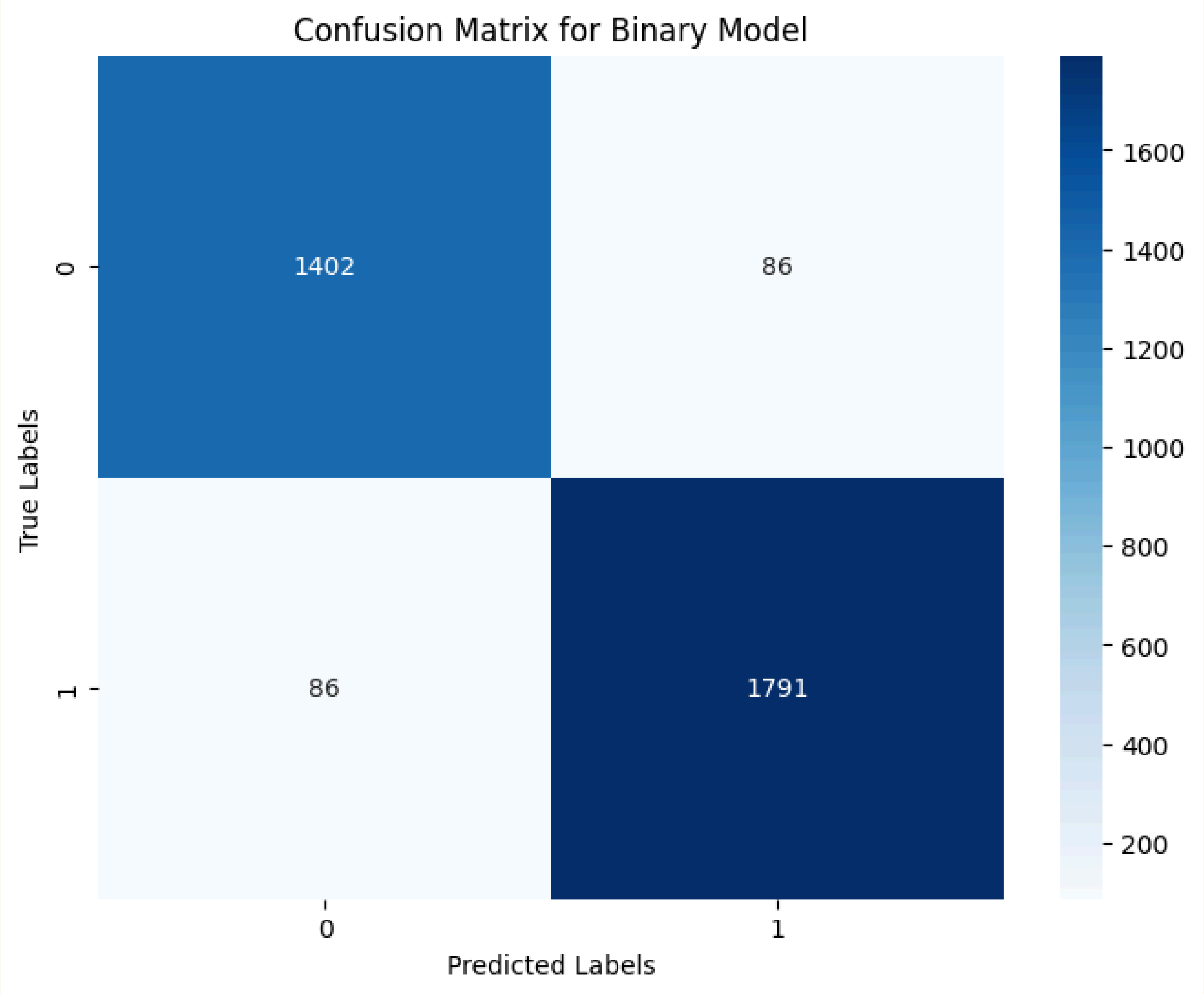
- TensorFlow and Keras were utilized for model training and development.
- Python was the main coding language.
- NumPy, Pandas, and Matplotlib assisted with data manipulation and result visualization.
- OpenCV and PIL were utilized for image preprocessing (resizing, normalization, and augmentation).
- Development was carried out in Jupyter Notebook or PyCharm for an easy coding experience.

PROTOTYPES

- Data Preprocessing: Established pipelines for resizing, normalizing, and augmenting images.
- Model Setup: Created a hybrid model integrating CNN, ViT, SSL, and Inception V3.
- Training: Model was trained on local systems without GPU acceleration.
- Model Testing:The performance was tested using Matplotlib and Seaborn to plot metrics.

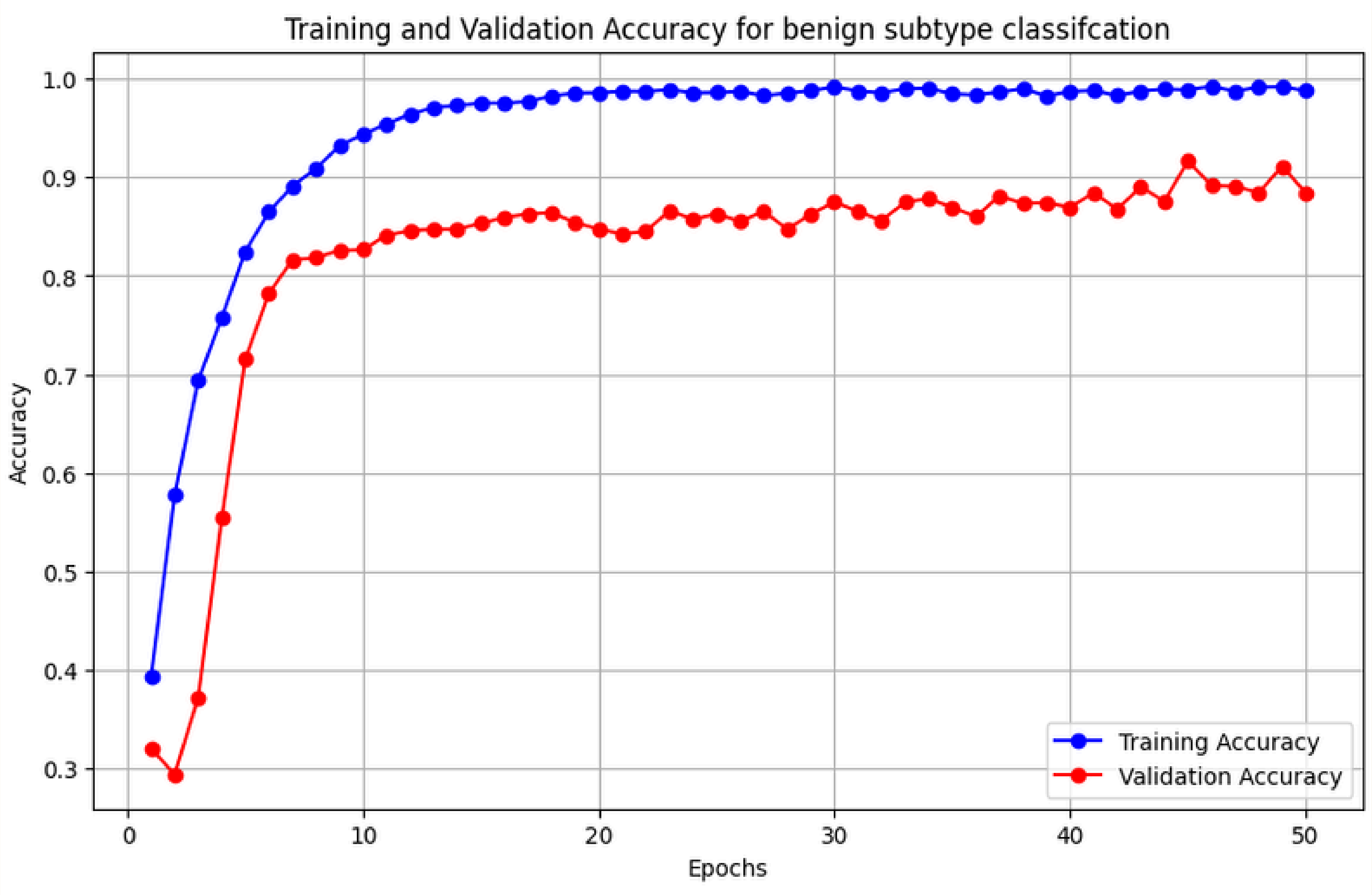
OVERALL CLASSIFICATION PERFORMANCE

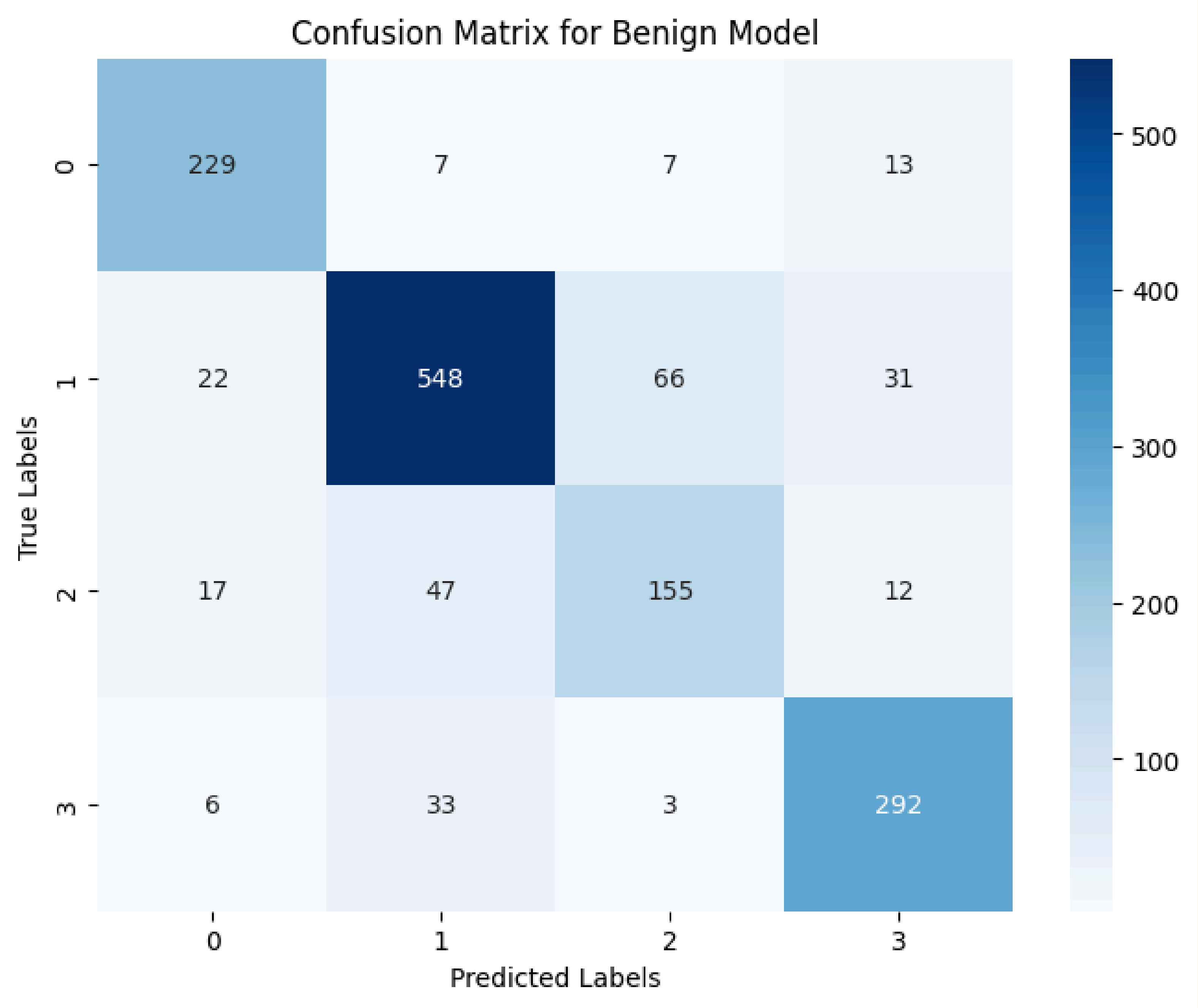




- **Precision: 0.9791**
- **Recall: 0.9712**
- **F1 Score: 0.9751**

The model achieved high precision and recall overall, indicating strong performance in identifying both classes accurately with minimal false positives and false negatives.



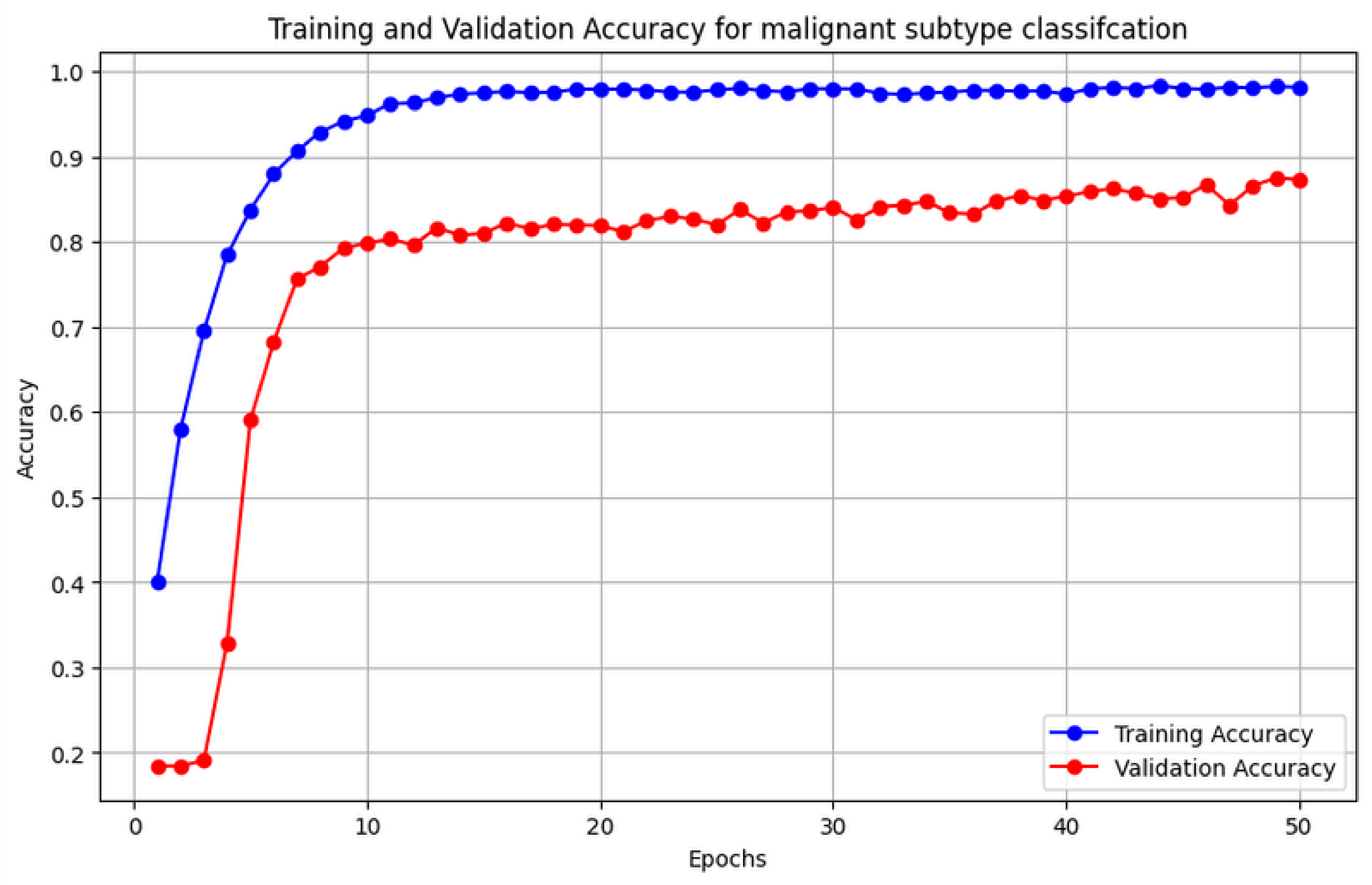


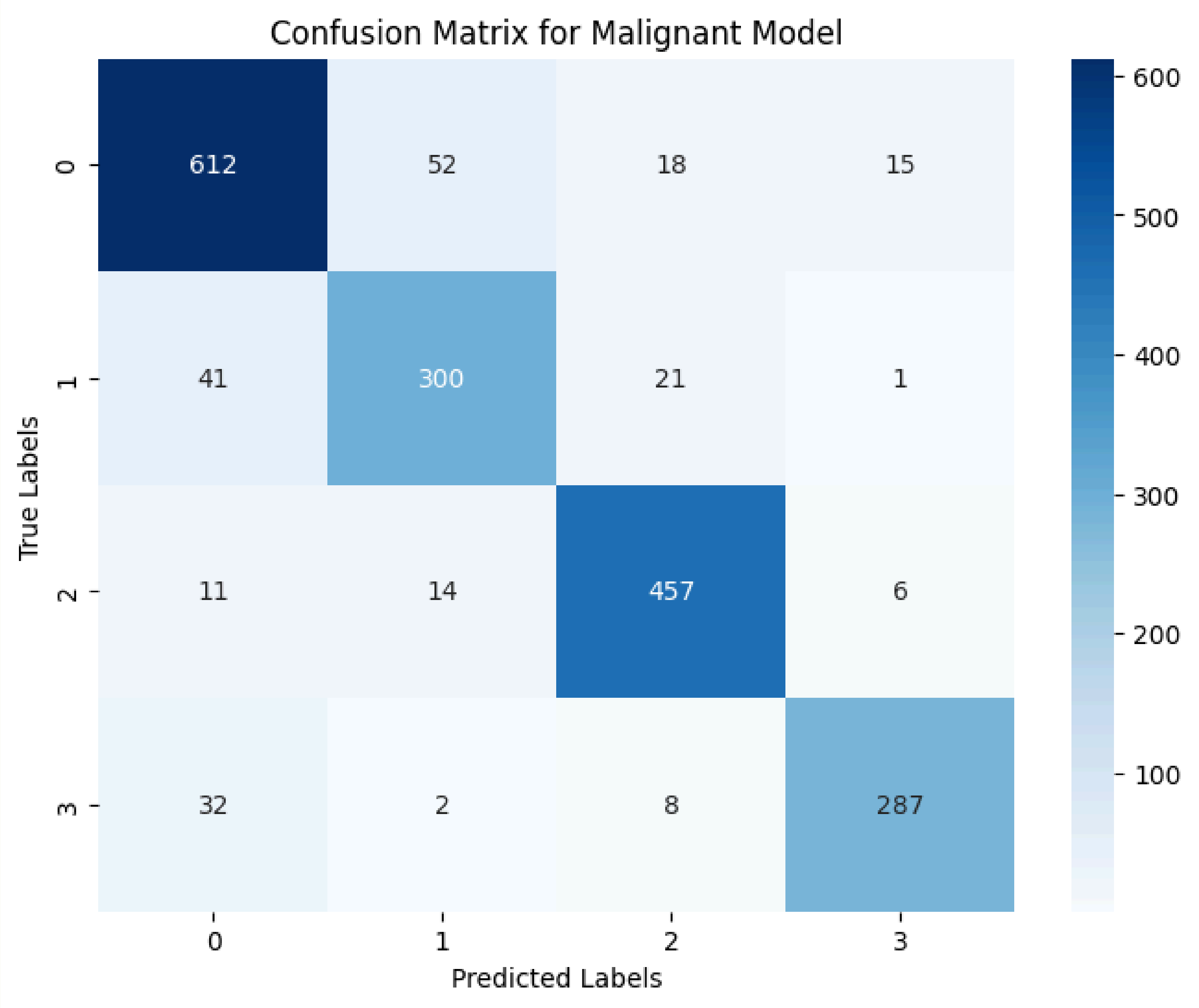
1. Benign Subtypes

(Includes: Adenosis, Fibroadenoma, Tubular Adenoma, Phyllodes Tumor)

- Precision: 0.8932
- Recall: 0.8592
- F1 Score: 0.8722

The model is effective in identifying benign tumors, but slightly lower recall suggests some benign cases are being misclassified as malignant. Precision remains strong, meaning most predictions for benign are correct.





2. Malignant Subtypes

(Includes: Ductal Carcinoma, Lobular Carcinoma, Mucinous Carcinoma, Papillary Carcinoma)

- Precision: 0.8825
- Recall: 0.8783
- F1 Score: 0.8801

Model performance on malignant tumors is quite balanced, with good precision and recall. It reliably detects malignant cases, which is crucial for early diagnosis and treatment.

ISSUES

- High Resource Utilization: The hybrid model was trained using ViT, SSL, and Inception V3, which demanded a lot of GPU power and time.
- Data Limitations: Restricted access to large, high-quality datasets and class imbalance problems impacted model accuracy and causes overfitting.
- Model Complexity: Debugging and tuning became harder due to the hybrid architecture, with issues of model interpretability.

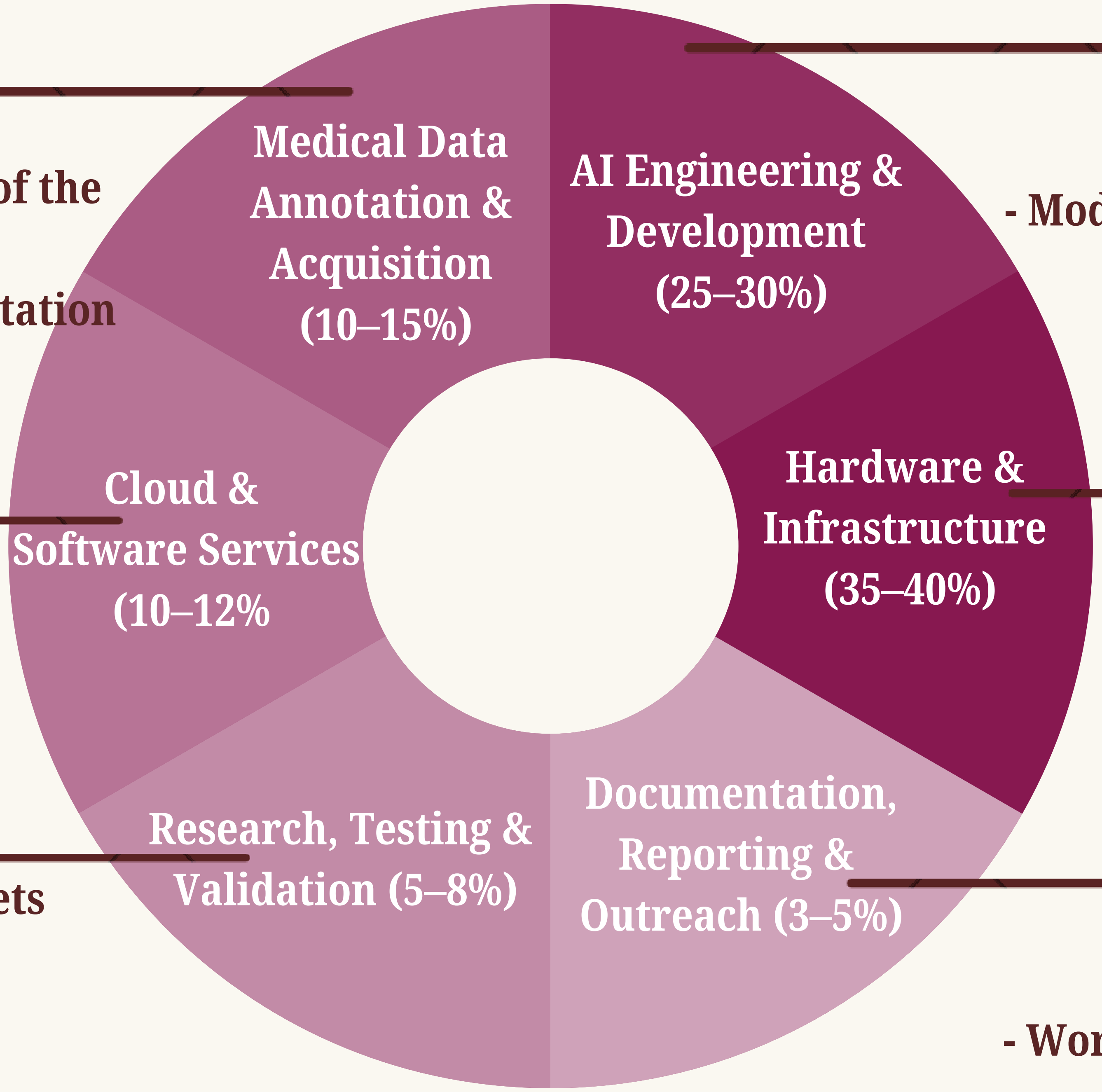
CONCLUSION

- **The hybrid model with ViT, SSL, and Inception V3 enhanced breast cancer diagnosis accuracy, given the difficulties with resources and data.**
- **Model interpretability and complexity are still weak points.**

Future Work:

- Optimize resources by enhancing model efficiency.
- Increase datasets to address class imbalance and data scarcity.
- Improve model interpretabilityfor clinician trust.
- Test in real-world clinical settings for improved generalizability.
- Update regularly with new data for continuous improvement.

TOTAL COST DISTRIBUTION



-Hospital/lab partnerships
- Cleaning, curation, anonymization of the data
- Time of expert pathologist for annotation
- Roughly ₹3–5 lakhs

- AI/ML engineer, data scientist, and software developer salaries
- Model development, training, validation, and optimization
- Roughly ₹8–12 lakhs

-Cloud services (AWS, GCP, Azure) for training and deployment
- APIs, model hosting platforms
- Approx. ₹2–4 lakhs

-High-end GPUs/TPUs (e.g., NVIDIA A100 or V100)
- Storage (local servers or cloud)
- Development workstations
- Roughly ₹10–15 lakhs

-Clinical validation with test datasets
- Cross-validation and regulatory compliance checks
- Approx. ₹1–2 lakhs

-Developing reports for researchers, policymakers
- Workshops, publications, knowledge sharing
- Approx. ₹50,000 – ₹1.5 lakhs

Estimated Total Cost: ₹25 – ₹40 lakhs

THANK YOU