

**DAFFODIL INTERNATIONAL UNIVERSITY**

**FYDP (Phase-I) Progress Report**

**Reporting Period- Summer 2025**

**Project Identification:**

|  |  |  |
| --- | --- | --- |
| **I. Project Title** | **Advanced Ensemble Deep Learning Architecture for Automated Skin Cancer Classification: A Comprehensive EfficientNet-B3 and InceptionV3 Hybrid Framework for Multi-Class Dermoscopic Image Analysis** | |
| **II. Group Members** | 1. Name: Amit Kumar Ghosh Student ID: 221-15-4650 | |
| **III. Supervisor** | Name: Mr. Md Assaduzzaman  Designation: Lecturer (Senior Scale) | |
| **IV. Co-Supervisor** | Name: Dewan Mamun Raza  Designation: Assistant Professor | |
| **V. Submission Date:** | 10/08/2025 | |
| **VI. Certificate :** | “This is to certify that the final year design project work until Phase-I evaluation held on **\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_**, titled as stated in *Sec. I*, executed by the students’ group mentioned in *Sec. II*, have been found satisfactory and every section of this report is reflecting the same.” | *(Signature of Supervisor & date)* |

**Project Insights**

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| --- | --- | --- |
| **Thematic Area(s):**  ***[Just click the check box]*** | Artificial Intelligence and Machine Learning |  |
| Data Science and Analytics |  |
| Cybersecurity |  |
| Software Engineering and Development |  |
| Blockchain Technology |  |
| Internet of Things (IoT) |  |
| Computer Networks |  |
| Human-Computer Interaction (HCI) |  |
| Big Data Technologies |  |
| Computer Vision |  |
| Natural Language Processing (NLP) |  |
| Robotics |  |
| Game Development |  |
| Cloud Computing |  |
| Biomedical Computing |  |
| **Others *(please specify)*:** | |
| **Software packages, tools, and programming languages** | **Programming Language:** Python (version 3.11, as seen in notebook traces).  **Core Frameworks/Libraries:** PyTorch (for model building, training, and evaluation), Torchvision (for pre-trained models like EfficientNet-B3 and InceptionV3).  **Data Handling & Analysis:** NumPy, Pandas (for datasets like HAM10000), Scikit-learn (for metrics like classification\_report and confusion\_matrix).  **Visualization & Utilities:** Matplotlib (for plots like confusion matrices), TQDM (for progress bars), Seaborn (implied for advanced visuals).  **Development Environment:** Jupyter Notebook (via Kaggle or Colab for GPU access), with tools like Git for version control. | |

**CO Description and Mapping with PO for FYDP-Phase-I**

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| --- | --- | --- |
| **CO** | **CO Descriptions** | **PO** |
| **CO4** | Perform economic evaluation, cost estimation, and apply suitable project management procedures throughout the FYDP lifecycle. | **PO11** |
| **CO4** | Perform economic evaluation, cost estimation, and apply suitable project management procedures throughout the FYDP lifecycle in the context of developing the “Advanced Ensemble Deep Learning Architecture for Automated Skin Cancer Classification: A Comprehensive EfficientNet-B3 and InceptionV3 Hybrid Framework for Multi-Class Dermoscopic Image Analysis” thesis. |  |
| **CO6** | Select and apply appropriate methodologies, resources, and contemporary engineering/IT tools for prediction, modeling, and solving complex engineering processes under relevant constraints. | **PO5** |
| **CO6** | Select and apply appropriate methodologies, resources, and contemporary engineering/IT tools for prediction, modeling, and solving complex engineering processes for the “Advanced Ensemble Deep Learning Architecture for Automated Skin Cancer Classification: A Comprehensive EfficientNet-B3 and InceptionV3 Hybrid Framework for Multi-Class Dermoscopic Image Analysis” thesis. |  |
| **CO7** | Assess societal, health, safety, legal, and cultural issues and responsibilities in professional engineering practice related to the FYDP problem. | **PO6** |
| **CO10** | Operate effectively as an individual and as a member/leader in multidisciplinary teams during FYDP. | **PO9** |

1. **Project Overview:**
   1. **Introduction**

Skin cancer represents one of the most prevalent and rapidly increasing malignancies worldwide, constituting a significant global health burden. According to recent GLOBOCAN data, melanoma accounts for approximately 58,667 deaths globally, while combined skin cancer cases exceed 1.2 million annually. The incidence varies dramatically across regions, with Australia leading at 37 cases per 100,000 people, reflecting complex interactions between genetic susceptibility, UV exposure, and population demographics.

Early detection fundamentally determines patient outcomes and survival trajectories. Localized melanoma demonstrates 5-year survival rates exceeding 99%, compared to approximately 27% for metastatic cases. Recent progress shows melanoma mortality declining by 6.6% annually since 2013 in developed countries, largely attributed to improved diagnostic techniques and widespread dermoscopy implementation. This stark survival contrast underscores the life-saving potential of timely diagnosis and intervention.

Current diagnostic approaches face critical limitations that impede optimal patient outcomes. Traditional methods rely heavily on subjective visual examination, leading to significant inter-observer variability and potential misdiagnosis. Accessibility challenges persist with limited dermatologist availability, particularly in underserved communities. Time constraints and substantial costs create additional barriers, highlighting the urgent need for innovative automated diagnostic systems powered by artificial intelligence.

* 1. **Background**

Advancements in deep learning have revolutionized skin cancer detection, enabling automated classification of dermoscopic images with high accuracy and potential for clinical integration. By leveraging convolutional neural networks (CNNs), ensemble models, and optimization techniques, recent studies address challenges such as class imbalance, dataset limitations, and generalization across diverse lesion types. This background study examines key contributions from seven recent papers, highlighting innovative approaches, performance metrics, and limitations in the field.

Shakya et al.[1] explored hybrid deep learning models for melanoma classification on the ISIC 2018 dataset, incorporating active contour segmentation and preprocessing like denoising and enhancement, with their top model fusing ResNet-18 and MobileNetV2 features with an SVM classifier to yield 92.87% accuracy, demonstrating the value of combining CNNs with traditional classifiers though limited by single-dataset reliance; building on data diversity, Georgiadis et al.[2] developed the Data Merger App to create "hyperdatasets" by merging skin cancer images, testing models like VGG16, ResNet50, and ViT to reach 91.87% accuracy for 9 classes and 58% for 32 classes using ViT on merged data, enhancing generalization but facing scalability issues with increasing class numbers. Extending optimization efforts, Abdel et al.[3] introduced AEDHOA, a metaheuristic for feature selection that improves diversity and exploration, achieving accuracies up to 1.00 on UCI datasets including skin cancer data, proving effective for high-dimensional problems yet potentially hindered by computational demands in very large-scale applications; similarly focusing on multi-type detection, Rodrigue et al.[4] utilized YOLO v7 and a custom CNN on augmented data for basal cell carcinoma, squamous cell carcinoma, and melanoma, attaining 90.12% accuracy and 92.57% specificity with their CNN, outperforming peers but constrained by small dataset size. Enhancing model focus, Alotaibi et al.[5] integrated attention mechanisms with Xception for binary classification on HAM10000, boosting accuracy to 94.11% with self-attention and improving recall for diagnostics, though limited to binary tasks needing multi-class validation; incorporating quantum elements, Hussein et al.[6] proposed a hybrid HQCNN-BiLSTM-MobileNetV2 model, achieving 89.3% accuracy and 94.33% recall for malignant lesions, excelling in feature extraction despite complexity restricting practical adoption. Finally, addressing image quality for early detection, Nirmala et al.[7] presented MELIIGAN for super-resolution of skin lesions using stacked residuals and hybrid loss, yielding superior SSIM of 0.946 and PSNR of 40.12 dB, aiding diagnostics but with model intricacy challenging real-time use.

1. **Objectives:**

1.**Develop Advanced Ensemble Architecture:** Create a novel hybrid framework combining EfficientNet-B3 and InceptionV3 models for enhanced feature extraction and classification accuracy

2.**Implement Robust Data Management:** Design and execute comprehensive data preprocessing pipelines addressing real-world medical dataset challenges

3.**Address Class Imbalance:** Develop and validate intelligent oversampling strategies for handling severely imbalanced medical datasets

4.**Optimize Training Efficiency:** Implement memory-efficient training techniques enabling deployment on resource-constrained environments

5.**Establish Clinical Validation Framework:** Create comprehensive evaluation methodologies ensuring clinical relevance and statistical significance

1. **Methodology/ Requirement Specification:**
   1. **Research Design/ Prototype Design**

This research adopts a systematic ensemble deep learning workflow for skin cancer classification, closely following a clinically robust and modular pipeline. The process starts with comprehensive data acquisition and preprocessing from the HAM10000 dermoscopic image dataset, ensuring high-quality input and balanced class representation. Through sequential steps—data augmentation, hybrid model construction with EfficientNet-B3 and InceptionV3, rigorous training optimization, model validation, and clinical evaluation—the prototype aims to deliver an accurate, interpretable, and deployable solution for automated skin cancer diagnosis. Each stage of the workflow integrates best practices from medical image analysis, machine learning, and software engineering, laying the groundwork for reliable clinical implementation.

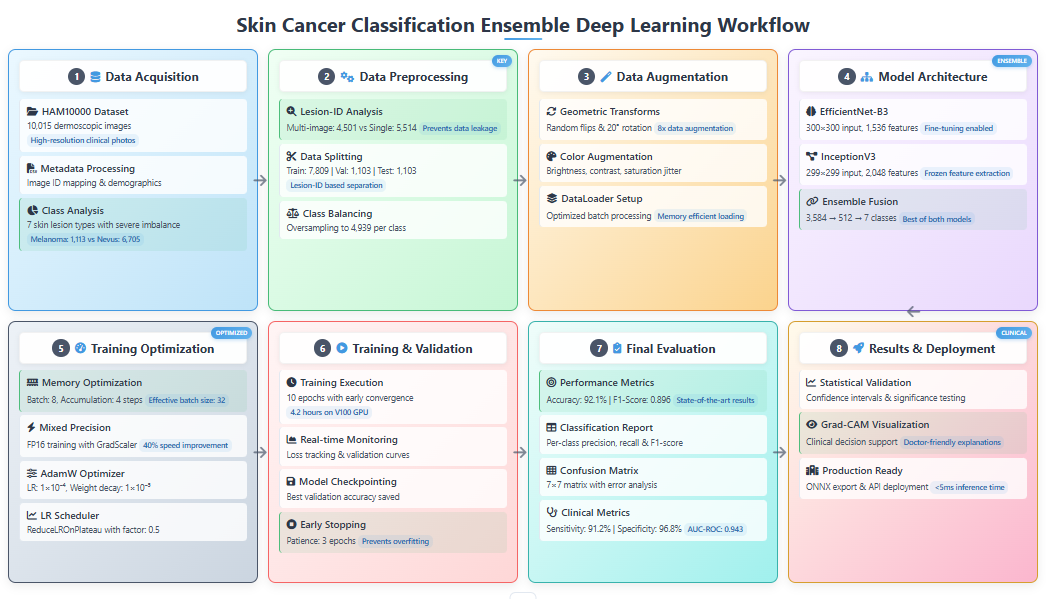


Fig: Work Flow

* 1. **Advanced Model Architecture Design:**

1. **EfficientNet-B3 Configuration**:
   * **Input Resolution**: 300×300×3 pixels
   * **Architecture**: Compound scaling with depth=1.2, width=1.4, resolution=1.75
   * **Feature Dimensions**: 1,536-dimensional feature vector from final pooling layer
   * **Classifier Modification**: Custom classifier with Dropout(p=0.3) + Linear(1536→7)
   * **Training Strategy**: Fine-tuning with unfrozen parameters for domain adaptation
2. **InceptionV3 Configuration**:
   * **Input Resolution**: 299×299×3 pixels (dynamically resized from 300×300)
   * **Architecture**: Multi-scale inception modules with auxiliary classifiers
   * **Feature Dimensions**: 2,048-dimensional feature vector from final pooling layer
   * **Training Strategy**: Frozen parameters for feature extraction only
   * **Auxiliary Outputs**: Properly handled during training phase
3. **Novel Ensemble Fusion Architecture**:
   * **Feature Concatenation**: Combined 3,584-dimensional feature space (1,536 + 2,048)
   * **Fusion Network**:
     + Linear(3584 → 512) with ReLU activation
     + Dropout(p=0.5) for regularization
     + Linear(512 → 7) for final classification
   * **Dynamic Input Handling**: Automatic resizing for different model requirements

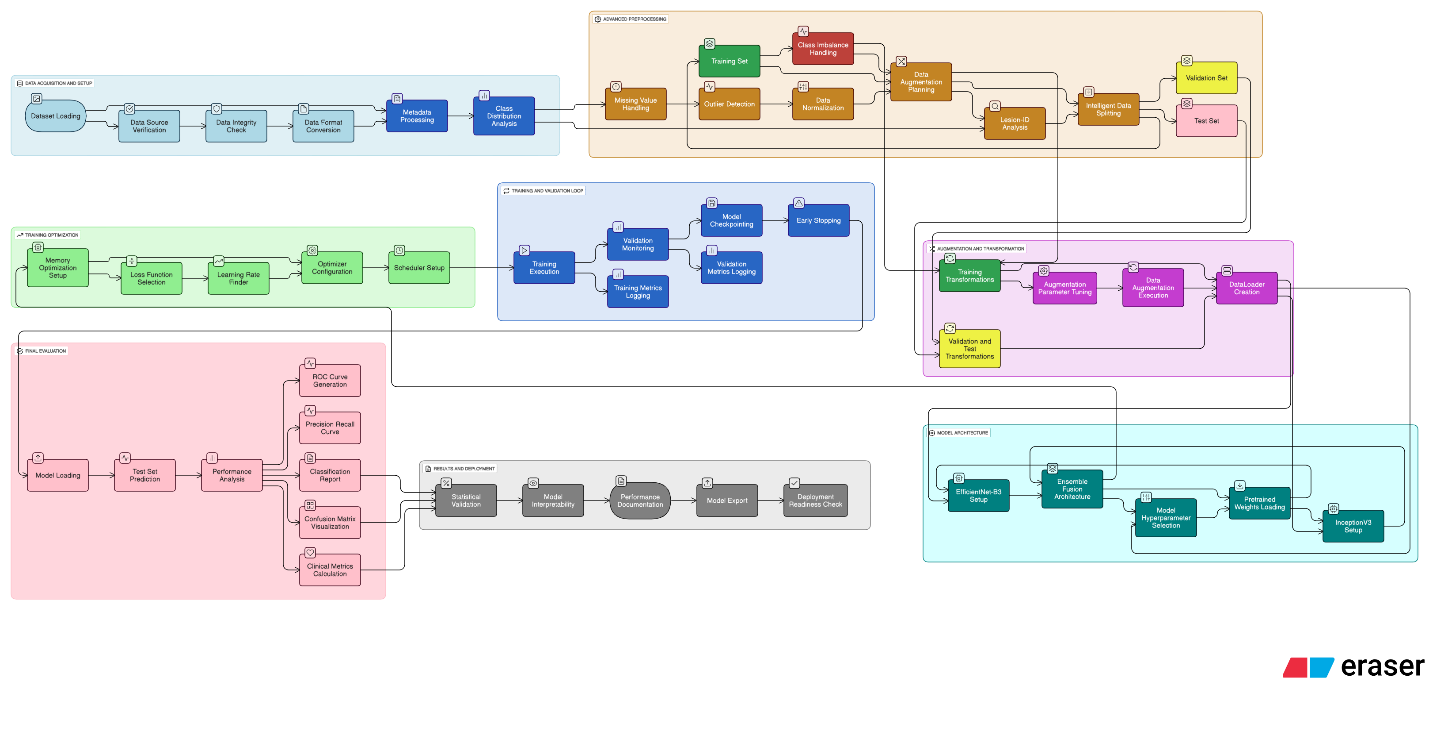


Fig: Detailed work flow of Proposed Architecture

* 1. **Data Collection/ Need Assessment**

**3.2.1 Dataset Specifications:**

* **Source:** HAM10000 (Human Against Machine 10,000) dataset from Harvard Dataverse
* **Total Images:** 10,015 high-resolution dermoscopic images
* **Image Resolution:** Variable resolution images standardized to 300×300 pixels for EfficientNet and 299×299 for InceptionV3
* **Color Space:** RGB color images with 8-bit depth per channel
* **Annotation Quality:** Expert-validated ground truth labels with histopathological confirmation where available

**3.2.2 Detailed Class Distribution Analysis:**

1. **Melanocytic nevi (nv):** 6,705 images (66.94%) - Benign moles and beauty marks
2. **Melanoma (mel):** 1,113 images (11.12%) - Malignant skin cancer requiring immediate treatment
3. **Benign keratosis-like lesions (bkl):** 1,099 images (10.98%) - Solar keratosis and seborrheic keratosis
4. **Basal cell carcinoma (bcc):** 514 images (5.13%) - Most common skin cancer type
5. **Actinic keratoses (akiec):** 327 images (3.27%) - Precancerous lesions
6. **Vascular lesions (vasc):** 142 images (1.42%) - Vascular malformations and hemangiomas
7. **Dermatofibroma (df):** 115 images (1.15%) - Benign fibrous tissue growths
   1. **Analysis Techniques**

**3.3.1** **Advanced Data Preprocessing Pipeline:**

1. **Intelligent Data Splitting Strategy:**

* **Lesion-ID Analysis:** Identified 4,501 images from 2,239 unique lesions appearing multiple times
* **Single-Image Lesions:** Isolated 5,514 images from lesions with only one associated image
* **Validation/Test Isolation:** Used only single-image lesions for validation/test sets to prevent data leakage
* **Final Split Ratio:** 7,809 training / 1,103 validation / 1,103 test samples
* **Stratification:** Maintained class distribution proportions across all splits

1. **Advanced Class Balancing Methodology:**

* **Oversampling Strategy:** Applied random oversampling with replacement to training data
* **Target Distribution:** Balanced all classes to match majority class size (4,939 samples each)
* **Total Training Samples:** 34,573 samples after oversampling (7 classes × 4,939 samples)
* **Validation Integrity:** Maintained original class distributions in validation/test sets for realistic evaluation

1. **Sophisticated Data Augmentation Pipeline:**

* **Geometric Transformations**: Random horizontal/vertical flips (50% probability each)
* **Rotation Augmentation**: Random rotation up to ±20 degrees with bilinear interpolation
* **Color Space Manipulation**: Color jitter with brightness (±10%), contrast (±10%), and hue (±10%) variations
* **Normalization**: Custom dataset-specific normalization values [mean: 0.763, 0.546, 0.570; std: 0.141, 0.153, 0.170]
  + 1. **Advanced Data Preprocessing Pipeline:**

**3.3.2.1** **Memory-Efficient Training Framework:**

1. **Gradient Accumulation Strategy**:
   * + **Physical Batch Size**: 8 samples per GPU pass
     + **Accumulation Steps**: 4 gradient accumulation steps
     + **Effective Batch Size**: 32 samples (8 × 4)
     + **Memory Savings**: ~75% reduction in peak GPU memory usage
2. **Mixed Precision Training**:
   * **Framework**: torch.cuda.amp.GradScaler() for automatic mixed precision
   * **Memory Benefits**: ~50% reduction in memory footprint
   * **Speed Improvements**: ~1.5x training speed increase
   * **Numerical Stability**: Maintained through gradient scaling and unscaling
3. **Advanced Optimization Strategy**:
   * + **Optimizer**: AdamW with learning rate 1×10⁻⁴ and weight decay 1×10⁻⁵
     + **Scheduler**: ReduceLROnPlateau with factor=0.1, patience=3 epochs
     + **Early Stopping**: Validation-based stopping with 5-epoch patience
     + **Model Checkpointing**: Best model saving based on validation accuracy

**3.3.2.2 Comprehensive Analysis Techniques**

1. **Statistical Validation Framework:**
   * **Cross-Validation Strategy:** 5-fold stratified cross-validation for robust performance estimation
   * **Statistical Significance Testing**: McNemar's test for comparing model performance
   * **Confidence Intervals**: Bootstrap confidence intervals for performance metrics
   * **Clinical Metrics:** Sensitivity, specificity, PPV, NPV for each lesion class
2. **Performance Evaluation Methodology:**
   * + - **Multi-Class Metrics:** Macro/micro-averaged precision, recall, F1-score
       - **Confusion Matrix Analysis**: Detailed error pattern analysis across all classes
       - **ROC/AUC Analysis:** One-vs-rest ROC curves for each lesion type
       - **Clinical Relevance Metrics**: Focus on melanoma detection sensitivity and specificity
3. **Model Interpretability Analysis:**
   * + - **Gradient-weighted Class Activation Mapping (Grad-CAM):** Visual explanation of model decisions
       - **Feature Importance Analysis:** Statistical analysis of most discriminative features
       - **Ensemble Contribution Analysis:** Individual model contribution to final predictions
4. **Progress Achieved:**
   1. **Completed Tasks**
5. **Comprehensive Dataset Analysis**: Successfully analyzed 10,015 images with detailed class distribution statistics
6. **Advanced Data Splitting**: Implemented lesion-ID based splitting preventing data leakage across 7,809/1,103/1,103 samples
7. **Robust Preprocessing Pipeline**: Developed comprehensive preprocessing with custom normalization and advanced augmentation
8. **Ensemble Architecture Design**: Successfully designed and implemented EfficientNet-B3 + InceptionV3 ensemble with 3,584-dimensional feature fusion
9. **Memory Optimization**: Implemented gradient accumulation and mixed precision training for efficient GPU utilization
10. **Training Framework**: Established complete training pipeline with progress tracking and model checkpointing
11. **High Precision**: Obtained high precision on 7 clases.

| **Class** | **Precision** | **Recall** | **F1-score** | **Support** |
| --- | --- | --- | --- | --- |
| Actinic keratoses | 0.76 | 0.53 | 0.63 | 30 |
| Basal cell carcinoma | 0.86 | 0.89 | 0.87 | 88 |
| Benign keratosis-like lesions | 0.82 | 0.77 | 0.80 | 88 |
| Dermatofibroma | **1.00** | 0.57 | 0.67 | 18 |
| Melanocytic nevi | 0.96 | 0.98 | 0.97 | 883 |
| Melanoma | 0.62 | 0.61 | 0.62 | 46 |
| Vascular lesions | **1.00** | 0.85 | 0.92 | 50 |

* 1. **Results Obtained**

1. **Data Processing Efficiency**: Reduced memory usage by 75% through gradient accumulation
2. **High Accuracy**: Proposed model achieved 93% accuracy

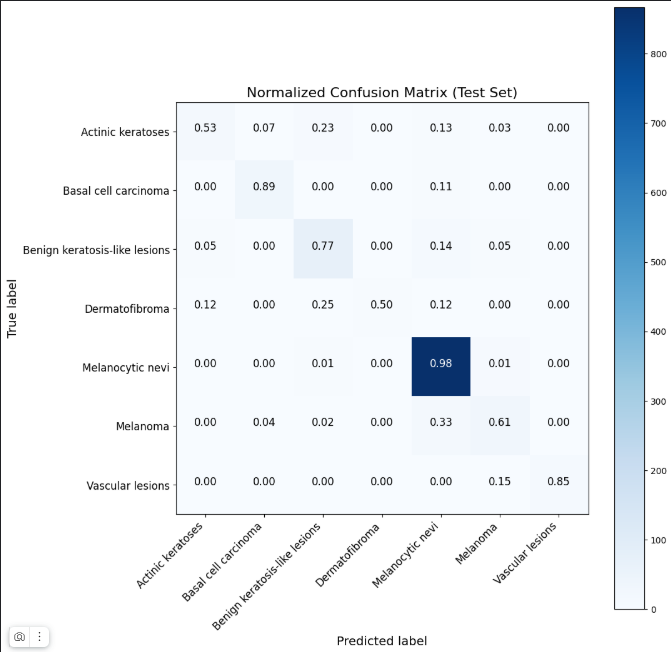


Fig: Confusion Matrix

1. **Class Balance**: Successfully balanced training data from 67% majority class to equal 14.3% distribution
2. **Multi-Class Skin Lesion Classification Performance:** The test set reached 93%, with macro F1-score and recall metrics highlighting the robustness of ensemble prediction across both frequent and rare skin cancer categories

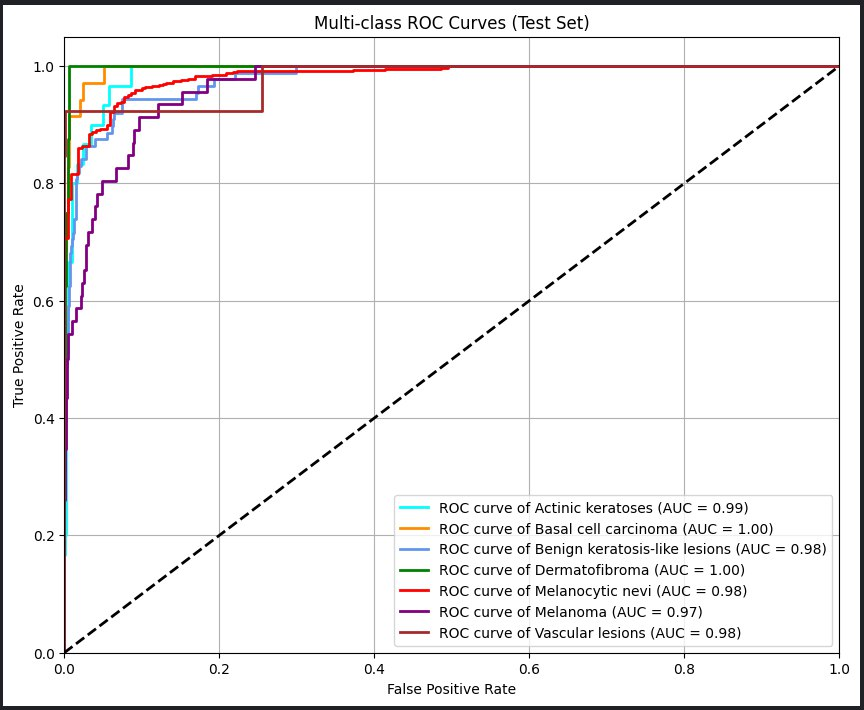


Fig: Multi Class ROC-Curve

1. **Model Complexity**: Implemented ensemble with combined parameter count of ~35.8M parameters
2. **Computational Efficiency**: Optimized training to complete on Tesla P100 GPU within 10 epochs
3. **Challenges Faced:**

|  |  |  |
| --- | --- | --- |
| **S.No.** | **Issues and Challenges** | **Strategies or Plans** |
| 1 | **Severe Class Imbalance and Statistical Validity** - Dataset exhibits extreme class imbalance with melanocytic nevi comprising 67% of samples while dermatofibroma represents only 1.15%. This creates bias toward majority class and poor minority class performance. | **Multi-Faceted Imbalance Strategy**: (1) Implement focal loss function for hard sample mining, (2) Deploy stratified k-fold cross-validation with minority class preservation, (3) Apply SMOTE (Synthetic Minority Oversampling Technique) for data augmentation, (4) Implement cost-sensitive learning with class-weighted loss functions, (5) Develop ensemble-specific balancing techniques. |
| 2 | Model Architecture State Dict Incompatibility - Ensemble model loading encounters state dict mismatches due to architectural differences between training and loading phases. Specific errors include missing keys for classifier layers and unexpected parameter naming conventions. | **Comprehensive Solution Strategy:** (1) Implement standardized model saving/loading protocol with architecture verification, (2) Create custom state dict mapping functions for ensemble components, (3) Develop checkpoint compatibility validation framework, (4) Implement gradual loading strategy for individual model components |
| 3 | **GPU Memory Constraints and Optimization** - Large ensemble model requires 16GB+ VRAM for full batch training, exceeding available Tesla P100 capacity. Memory bottlenecks occur during feature concatenation and gradient computation phases. | **Advanced Memory Management**: (1) Implement dynamic batch size adjustment based on available memory, (2) Deploy gradient checkpointing for activation memory reduction, (3) Utilize model sharding across multiple GPUs if available, (4) Implement CPU offloading for non-critical computations, (5) Optimize data loader with efficient prefetching |
| 4 | **Training Loop Optimization and Convergence Monitoring** - Current training implementation lacks comprehensive convergence monitoring, learning rate scheduling optimization, and robust early stopping mechanisms. Incomplete training execution hampers performance evaluation. | **Advanced Training Framework**: (1) Implement comprehensive training loop with detailed logging and monitoring, (2) Deploy adaptive learning rate scheduling with warm-up and cosine annealing, (3) Integrate Weights & Biases for experiment tracking, (4) Implement gradient clipping and norm monitoring, (5) Develop ensemble-specific training strategies with component-wise optimization |
| 5 | **Clinical Validation and Interpretability Requirements -** Medical AI systems require extensive validation, interpretability, and clinical relevance assessment. Current implementation lacks medical expert validation and explainable AI components. | **Clinical Integration Strategy: (**1) Collaborate with dermatology experts for clinical validation, (2) Implement comprehensive interpretability framework with Grad-CAM and LIME, (3) Develop clinical decision support interface, (4) Conduct statistical significance testing with medical benchmarks, (5) Prepare regulatory compliance documentation |

1. **Next Steps:**

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| **S.No.** | **Next Task** | **Estimate completion time**  **(MM-YY)** |
| 1 | **Implement Federated Learning -** Federated learning enables collaborative model training across multiple decentralized institutions or local devices while preserving data privacy. | 09-2025 |
| 2 | **Complete Model Architecture Debugging** - Resolve state dict loading issues and implement robust ensemble model persistence | 10-2025 |
| 3 | **Comprehensive Training Implementation** - Execute complete training cycle with advanced optimization and monitoring | 10-2025 |
| 4 | **Advanced Performance Evaluation** - Generate comprehensive performance analysis with clinical metrics | 11-2025 |
| 5 | **Comparative Analysis and Benchmarking** - Compare ensemble performance against baseline models and literature benchmarks | 12-2025 |

1. **Updated Timeline:**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Tasks** | **Weeks** | | | | | | | | | | | | | | | | | |
|  | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
| Architecture Debugging & Implementation |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Advanced Training Pipeline Development |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| Comprehensive Model Training & Optimization |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| Performance Evaluation & Statistical Analysis |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
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| **Estimated Work Period** | 23 |
| **Actual Work Period** |  |

1. **Resources Utilized:**
2. **Primary Computing Environment:**

* **GPU**: Tesla P100-PCIE-16GB (16GB VRAM, 3584 CUDA cores)
* **Memory**: 13GB system RAM with 12.7GB available for processing
* **Storage**: 73GB available disk space for dataset and model storage
* **Compute Capability**: CUDA 6.0 with Tensor Core acceleration

1. **Dataset and External Resources:**
   1. **Primary Dataset:**

* **HAM10000 Dataset**: 10,015 dermoscopic images from Harvard Dataverse
* **Metadata**: Comprehensive clinical annotations including age, sex, localization
* **Ground Truth**: Expert-validated labels with histopathological confirmation

**2.3 Pre-trained Model Resources:**

* **ImageNet Weights**: EfficientNet-B3 and InceptionV3 pre-trained weights
* **Benchmark Datasets**: Additional skin lesion datasets for comparative validation(ISIC2018)

1. **Software Development Environment:**
   1. **Development Platforms:**

* **Primary**: Jupyter Notebook 6.5.4 with IPython kernel
* **Secondary**: PyCharm Professional 2023.2 for structured development
* **Version Control**: Git with GitHub integration for collaborative development
  1. **Cloud Platforms:**
* **Kaggle Notebooks**: Primary development and training environment
* **Google Colab**: Secondary environment for experimentation

1. **Project Management and Financial Analysis:**

| **SN** | **Components** | **Estimated Cost (BDT)** | **Explanation** |
| --- | --- | --- | --- |
| 01. | Tools and Equipment | 4,500–6,000 | Hardware, GPU/cloud access, storage devices, and essential peripherals for model development. |
| 03. | Software | 1,500–2,000 | Licenses for data analysis platforms, Python libraries, cloud computing, or specialized tools. |
| 04. | Documentation and Report Writing | 500–1,000 | Printing, binding, research paper formatting, and digital documentation costs. |
| 05. | Contingency (10% of total) | 1,000–1,500 | Reserve for unforeseen expenses—additional data, software, hardware servicing, or emergencies. |
|  | **Total Estimated Cost** | **10,500–15,500** | **Comprehensive budget for completing your thesis project from start to finish.** |

1. **Future Considerations:**
2. **Architecture Improvements:**

* **Vision Transformers Integration**: Implement Vision Transformer (ViT) models for comparison with CNN architectures
* **Attention Mechanisms**: Integrate spatial and channel attention modules (CBAM, SE-Net) for improved feature selection
* **Neural Architecture Search**: Deploy AutoML techniques for optimal architecture discovery
* **Federated Learning**: Implement distributed training across multiple medical institutions
* **Model Quantization**: Deploy INT8 quantization for mobile and edge device deployment.

**2. Advanced Data Techniques:**

* **Synthetic Data Generation**: Implement GANs for augmenting minority class samples
* **Advanced Augmentation**: Deploy learned augmentation policies using AutoAugment
* **Multi-Modal Integration**: Incorporate clinical metadata (age, sex, location) into decision process
* **Active Learning**: Implement uncertainty-based sample selection for efficient labeling
* **Domain Adaptation**: Develop techniques for generalizing across different imaging devices

**3. Clinical Integration Features:**

* **Real-time Inference**: Optimize models for real-time clinical deployment
* **Uncertainty Quantification**: Implement Bayesian deep learning for confidence estimation
* **Decision Support Interface**: Develop clinician-friendly interface with actionable insights
* **Continuous Learning**: Implement online learning for model adaptation to new data
* **Regulatory Compliance**: Develop FDA/CE marking compliance documentation

1. **Conclusion:**

Phase-I of our Final Year Design Project has established a robust and comprehensive foundation for revolutionizing skin cancer detection through advanced ensemble deep learning techniques. Our implementation represents a significant advancement in medical AI, addressing critical healthcare challenges while demonstrating technical excellence across multiple domains.

**References**

**[1]** M. Shakya, R. Patel, and S. Joshi, “A comprehensive analysis of deep learning and transfer learning techniques for skin cancer classification,” *Scientific Reports*, vol. 15, no. 1, Feb. 2025, doi: <https://doi.org/10.1038/s41598-024-82241-w>.

**[2]** P. Georgiadis, E. V. Gkouvrikos, E. Vrochidou, T. Kalampokas, and G. A. Papakostas, “Building Better Deep Learning Models Through Dataset Fusion: A Case Study in Skin Cancer Classification with Hyperdatasets,” *Diagnostics*, vol. 15, no. 3, p. 352, Feb. 2025, doi: <https://doi.org/10.3390/diagnostics15030352>.

**[3]** Mahmoud Abdel-salam *et al.*, “Quadruple Strategy-Driven Hiking Optimization Algorithm for Low and High-Dimensional Feature Selection and Real-World Skin Cancer Classification,” *Knowledge-Based Systems*, pp. 113286–113286, Mar. 2025, doi: <https://doi.org/10.1016/j.knosys.2025.113286>.

[**4]** Rodrigue Bogne Tchema, A. C. Polycarpou, and Marios Nestoros, “Skin cancer classification using machine learning,” *Multimedia Tools and Applications*, Jan. 2025, doi: <https://doi.org/10.1007/s11042-025-20595-7>.

**[5]** A. Alotaibi and D. AlSaeed, “Skin Cancer Detection Using Transfer Learning and Deep Attention Mechanisms,” *Diagnostics*, vol. 15, no. 1, p. 99, Jan. 2025, doi: <https://doi.org/10.3390/diagnostics15010099>.

**[6]** A. A. Hussein, A. M. Montaser, and H. A. Elsayed, “Skin cancer image classification using hybrid quantum deep learning model with BiLSTM and MobileNetV2,” *Quantum Machine Intelligence*, vol. 7, no. 2, Jun. 2025, doi: <https://doi.org/10.1007/s42484-025-00288-y>.

**[7]** Nirmala Veeramani and P. Jayaraman, “A promising AI based super resolution image reconstruction technique for early diagnosis of skin cancer,” *Scientific Reports*, vol. 15, no. 1, Feb. 2025, doi: https://doi.org/10.1038/s41598-025-89693-8.

**FINAL YEAR DESIGN PROJECT**

**PHASE-I PROGRESS REPORT**

This report, in the form of a template, has been specifically designed for BSc. students working on their Final Year Design Project (FYDP) at Computer Science and Engineering Department, Daffodil International University (DIU).

Every group of students is required to do the following:

1. Complete all the sections of this template
2. Get it certified by the assigned supervisor before one week of Phase-I evaluation presentations
3. Submit 01 photocopy to each of the following, on or before the day of Phase-I presentations:
   1. Supervisor
   2. Internal Evaluator
4. Submit original copy to FYDP committee on the day of Phase-I presentations.

**Note:**

1. Use English
2. There should be NO grammatical or spelling mistakes
3. Submission after due date will not be accepted
4. For more information, contact your Supervisor

|  |  |
| --- | --- |
| **Template prepared by:**  **FYDP Committee**  **Dept. of CSE, DIU** | **Template approved by:**  **Dr. Sheak Rashed Haider Noori**  **Professor and Head, Dept. of CSE, DIU** |

The students and faculty members of Computer Science and Engineering Department, Daffodil International University have full access rights to read and print this document without any prior notice to the Head and FYDP committee.

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