PROJECT REPORT

EEE 4709

Artificial Intelligence & Machine Learning

Project Title: Lightweight Deep Learning Model for Skin Cancer Detection using Knowledge Distillation

Group No: C6

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Abstract

Skin cancer is one of the most prevalent and life-threatening forms of cancer worldwide, affecting millions of people each year. Early detection plays a vital role in improving treatment outcomes and increasing survival rates. However, access to dermatologists and advanced diagnostic tools remains a challenge, especially in remote and underserved areas. This project aims to address this gap by developing a lightweight, deep learning-based skin cancer detection system that is optimized for deployment on edge devices such as smartphones and tablets, making early diagnosis more accessible and affordable.

The system leverages knowledge distillation, a technique that transfers knowledge from a large, complex deep learning model (the teacher model) to a smaller, more efficient model (the student model). This approach ensures that the lightweight model retains high accuracy while significantly reducing computational costs, making it ideal for real-world applications. The HAM10000 dataset, a well-known collection of dermatoscopic images, is used for training and validation, providing a diverse and representative sample of skin lesions.

To enhance performance, this project incorporates CNN architectures, ensemble learning, and transfer learning techniques, enabling the model to learn robust feature representations. The use of data augmentation and advanced preprocessing techniques ensures improved generalization across different skin types and lesion characteristics. Additionally, model optimization strategies such as quantization and pruning are applied to further enhance efficiency without compromising accuracy.

A web-based application is developed and deployed, allowing users to easily upload images of skin lesions for classification. The system provides real-time predictions, displaying the most likely diagnosis along with confidence scores. This feature makes it a valuable tool for both individuals and healthcare professionals, assisting in preliminary screenings and reducing the burden on medical facilities.

Experimental results demonstrate that the lightweight model performs competitively with state-of-the-art deep learning models, achieving high classification accuracy while maintaining computational efficiency. The system's ability to run on low-power devices makes it particularly suitable for mobile healthcare applications, enabling remote diagnostics and early intervention in resource-constrained environments.

By bridging the gap between advanced AI technology and practical healthcare solutions, this project has the potential to revolutionize skin cancer detection, making high-quality diagnostics more accessible to a global population. Future improvements

will focus on expanding the dataset, improving class balance, integrating explainability techniques, and enhancing real-time usability to further refine the system's accuracy and reliability.

1. Introduction

1.1 Background and Motivation

Skin cancer is one of the most prevalent and life-threatening diseases worldwide. According to the World Health Organization (WHO), millions of new cases of skin cancer are diagnosed annually, with melanoma being the deadliest form. Early detection is critical for improving patient survival rates, as early-stage melanoma has a five-year survival rate exceeding 95%, whereas late detection significantly reduces treatment success.

Traditional methods for diagnosing skin cancer involve visual examination by dermatologists followed by biopsy confirmation. However, this process is not only time-consuming and expensive but also highly subjective, leading to variability in diagnosis. Additionally, access to specialized dermatologists is limited in many remote and underdeveloped regions, making early diagnosis difficult for a significant portion of the population.

With the advancements in artificial intelligence (AI) and deep learning, computer-aided diagnosis (CAD) systems have emerged as a promising solution for automating medical image classification. CNN-based models have demonstrated dermatologist-level accuracy in detecting various types of skin lesions, significantly improving early diagnosis and reducing human error. However, despite their effectiveness, deep learning models often require substantial computational power, making them impractical for real-time applications, particularly on mobile and low-resource devices.

This project aims to bridge the gap between high-performance deep learning models and real-time, deployable solutions by implementing knowledge distillation. This technique allows a smaller, lightweight student model to mimic the behavior of a larger, high-performing teacher model, thereby ensuring accurate predictions while reducing computational costs.

1.2 Problem Statement

Despite the success of deep learning in skin cancer classification, several key challenges remain unaddressed:

- High Computational Cost – Traditional deep learning models, such as ResNet50 and DenseNet169, are computationally intensive and require powerful GPUs, making real-time deployment difficult.

- Limited Accessibility – Most existing AI-driven skin cancer detection models are designed for clinical and research settings, but they are not optimized for low-resource environments or mobile deployment.

- Lack of Generalization – Some models struggle with real-world generalization, particularly when applied to diverse populations with different skin tones.

- Model Interpretability – AI-based diagnostic systems often function as black-box models, making it difficult for dermatologists and healthcare professionals to interpret model decisions and trust predictions.

This project aims to solve these problems by leveraging knowledge distillation to compress a deep learning model while maintaining high accuracy, allowing for real-time, efficient, and accessible deployment in telemedicine applications.

1.3 Objectives

The primary objective of this project is to develop a lightweight yet accurate deep learning model for automated skin cancer classification. The following goals are set to achieve this outcome:

- Develop a High-Accuracy Teacher Model – Train a ResNet50 and DenseNet169 model on the HAM10000 dataset to achieve state-of-the-art classification performance.

- Implement Knowledge Distillation – Transfer knowledge from the teacher model to a MobileNetV2 student model, ensuring reduced computational complexity while maintaining classification accuracy.

- Enhance Model Robustness Using Ensemble Learning – Combine ResNet50, DenseNet169, and MobileNetV2 predictions to improve overall classification accuracy.
- Optimize the Model for Low-Power Devices – Ensure that the final model can be deployed on mobile and edge devices for real-time inference without requiring high-end hardware.

This project will provide a scalable, efficient, and accurate AI-based solution for skin cancer detection, making early diagnosis more accessible to underserved populations.

1.4 Scope and Limitations

Scope of the Project:

The focus of this project is on automated classification of skin cancer lesions using deep learning and knowledge distillation. The following aspects define the scope of the study:

- The project is limited to seven types of skin lesions, as provided by the HAM10000 dataset.
- The classification process is based on dermatoscopic images rather than clinical photographs or microscopic scans.
- The primary deep learning models used are ResNet50, DenseNet169, and MobileNetV2, with knowledge distillation applied to compress MobileNetV2 for deployment.

Limitations of the Project:

Despite the advancements in deep learning, the proposed system has certain limitations:

- Dataset Bias – The HAM10000 dataset consists primarily of light-skinned individuals, which may reduce the model's accuracy when applied to darker skin tones.
- No Lesion Segmentation – The model classifies entire images but does not segment the lesion area, which could improve diagnostic accuracy.
- Computational Constraints – Although knowledge distillation significantly reduces the model size, real-time inference on extremely low-end devices (e.g., Raspberry Pi) may still experience performance bottlenecks.
- Model Confidence and Explainability – While the AI model provides classification predictions, it does not offer explainability features (e.g., heatmaps) to show which parts of the image influenced the decision.

2. Literature Review

2.1 Existing Studies

Deep Learning for Skin Cancer Detection

Skin cancer detection using deep learning-based computer-aided diagnosis (CAD) systems has gained significant attention in recent years. Convolutional Neural Networks (CNNs) have demonstrated state-of-the-art performance in classifying dermatoscopic images. Unlike traditional feature extraction methods, CNNs learn hierarchical patterns from images, making them highly effective for medical image classification.

Studies have shown that deep learning models trained on large dermatology datasets can achieve dermatologist-level accuracy in skin cancer detection. A pioneering study by Esteva et al. (2017) used InceptionV3 trained on 129,450 clinical images across 2,032 diseases and demonstrated comparable performance to board-certified dermatologists. Since then, more powerful architectures like ResNet, MobileNet, and DenseNet have been explored to improve accuracy while optimizing computational efficiency.

ResNet50 in Medical Imaging

The ResNet (Residual Network) architecture, introduced by He et al. (2016), introduced skip connections to solve the vanishing gradient problem, enabling the training of very deep networks. The ResNet50 model has been widely used in skin cancer classification due to its ability to extract robust features from medical images. Several studies have applied transfer learning on ResNet50, pre-trained on ImageNet, to classify benign and malignant skin lesions with high accuracy. However, ResNet50 is computationally expensive, requiring high-end GPUs for efficient inference.

DenseNet169 for Feature Extraction

The DenseNet (Densely Connected Convolutional Networks), proposed by Huang et al. (2017), introduced a densely connected block structure where each layer receives input from all previous layers. This design improves gradient flow and feature reuse, making DenseNet particularly useful for medical image analysis. DenseNet169 has been successfully applied in skin lesion classification, showing improvements in both accuracy and computational efficiency compared to ResNet. The dense connections also allow for better feature propagation, reducing the number of parameters while maintaining high representational power.

MobileNetV2 for Lightweight Applications

While ResNet and DenseNet provide high accuracy, they remain computationally expensive for mobile or real-time applications. To address this, MobileNetV2 was introduced by Sandler et al. (2018), designed specifically for low-power devices. It utilizes depth wise separable convolutions, significantly reducing the number of parameters while maintaining classification accuracy.
MobileNetV2 has been explored in skin cancer classification, particularly in scenarios where real-time inference is required, such as telemedicine applications. However, due to its smaller capacity, MobileNetV2 alone may underperform compared to larger models. This limitation motivates the use of knowledge distillation, where a larger teacher model (ResNet50/DenseNet169) transfers knowledge to a compact student model (MobileNetV2) to balance accuracy and efficiency.

2.2 Comparison with Existing Work

Compared to prior work:

- Our project focuses on knowledge distillation, which is rarely used in skin cancer detection.
- We integrate ensemble learning to improve robustness.
- Custom KD implementation combining ResNet50 and MobileNetV2.
- Emphasis on parameter reduction (92% fewer parameters than ResNet50).
- Comprehensive evaluation of class-wise performance despite dataset imbalance.
- A web-based deployment ensures real-world usability.

Unlike previous works, this project integrates knowledge distillation to transfer knowledge from high-performing teacher models (ResNet50 and DenseNet169) to a lightweight student model (MobileNetV2), ensuring high accuracy with significantly reduced computational cost. Additionally, ensemble learning is applied to leverage the strengths of multiple architectures, improving robustness in classification. Furthermore, while most research focuses on training models, making skin cancer detection accessible and scalable for clinical and telemedicine applications.

3. System Architecture/Experimental Setup

3.1 Overall System Design

Our system follows a three-stage pipeline:

- Teacher Model: ResNet50 and DenseNet169 pre-trained on ImageNet, fine-tuned on HAM10000.
- Student Model: MobileNetV2 with custom layers (Global Average Pooling, Dense, Dropout).
- KD Workflow:
- Soft Labels: Teacher-generated probabilistic outputs (temperature scaling: T=50).
- Hybrid Loss: $L_{KD} = \alpha \cdot L_{CE} + (1-\alpha) \cdot L_{KL}$ where $\alpha = 0.8$

3.2 Hardware and Software Requirements

- Hardware: NVIDIA GPU (for training), CPU (for web app deployment).
- Software: Python, TensorFlow, Flask, OpenCV.

3.3 Data Sources and Preprocessing

- HAM10000: 10,015 images across 7 classes.
- Preprocessing:
- Resizing (224x224), normalization (pixel values scaled to [0,1]).
- Augmentation: Rotation (±20°), horizontal flip, brightness adjustment.
- Class Balancing: Oversampling minority classes to 1,200 samples each

4. Methodology

4.1 Theoretical Foundations

Deep Learning for Medical Image Classification

Deep learning has revolutionized medical imaging by enabling automated, high-accuracy classification of diseases. Convolutional Neural Networks (CNNs) have proven particularly effective in diagnosing skin cancer from dermatoscopic images. CNNs extract hierarchical features from input images, such as texture, shape, and patterns, allowing them to learn complex representations that help differentiate between benign and malignant lesions. However, deep CNNs, such as ResNet50, require extensive computational power, making real-time deployment difficult, especially on low-resource devices.

To address this issue, knowledge distillation is used to compress a large, high-performing teacher model (ResNet50) into a smaller student model (MobileNetV2) while retaining predictive accuracy. This technique ensures that the student model maintains robust classification performance while being computationally efficient.

Knowledge Distillation

Knowledge distillation is a technique where a large, pre-trained model (teacher) transfers its knowledge to a smaller model (student). The key idea is to use the teacher's soft probabilities (logits) instead of just hard labels to train the student model. The student learns not only the final class labels but also the inter-class relationships captured by the teacher.

Knowledge Distillation Loss,

$L_{KD} = \alpha \cdot \text{CrossEntropy}(y_{true}, y_{student}) + (1-\alpha) \cdot \text{KL - Divergence}(y_{teacher}, y_{student})$

Temperature Scaling: Softens teacher logits to $y_{teacher} = \text{softmax}(\text{logits}/T)$

Ensemble Learning for Robust Predictions

To improve classification performance, an ensemble learning approach is applied. Instead of relying on a single model, multiple predictions from different architectures (ResNet50, MobileNetV2) are combined to reduce errors.

4.2 Experimental Setup/Algorithm

Dataset and Preprocessing:

The HAM10000 dataset is used for training and evaluation. It contains 10,015 labeled images of seven different types of skin lesions. The dataset is preprocessed as follows:

- Resizing: All images are resized to 224×224 pixels to match ResNet50, DenseNet169 and MobileNetV2 input requirements.
- Normalization: Pixel values are scaled to [0,1] to improve training stability.
- Augmentation: Techniques such as random flipping, rotation, and zooming are applied to enhance model generalization.

Train-test split:

This part splits the dataset into three subsets:

- 80% Training Set
- 20% Testing Set
- From the 80% Training Set, another split is done:
    - 80% for Actual Training
    - 20% for Validation

To ensure proper model training and evaluation, the dataset was split into three parts:

1. **Training Set (64%)** – Used for model training.
2. **Validation Set (16%)** – Used for hyperparameter tuning and avoiding overfitting.
3. **Test Set (20%)** – Used for final model evaluation.

The dataset splitting was performed using Stratified Sampling to maintain class balance across sets. The train_test_split() function from Scikit-Learn was used to achieve this in two steps:

Step 1: Initial Split into Training and Testing Sets

The first split allocated 80% of the dataset for training and 20% for testing to ensure a fair evaluation. The stratified sampling technique was applied to maintain the distribution of skin lesion classes across the splits.

Step 2: Splitting the Training Set into Training and Validation Sets

From the 80% training data, a further split was performed to separate 80% for actual training and 20% for validation.

Data Augmentation

To improve the generalization capability of the deep learning model, data augmentation was applied to the training dataset using **Keras ImageDataGenerator**. This technique artificially increases the dataset size by applying random transformations to the images, thereby helping the model generalize better to unseen data.

The following augmentations were applied:

- **Rescaling:** Each image's pixel values were normalized to the range **[0, 1]** by dividing by 255.
- **Rotation:** Images were randomly rotated within a range of **±5 degrees**.
- **Brightness Adjustment:** Brightness was varied between **85% and 115%** of the original value.
- **Shifting:** The images were translated horizontally and vertically by **2% of their dimensions**.
- **Shearing:** A shear transformation of **10 degrees** was applied.
- **Zooming:** Images were randomly zoomed in/out by **20%**.
- **Flipping:** Horizontal flipping was enabled to introduce variation in lesion orientations.

These augmentations ensured the model trained on diverse variations of skin lesion images, reducing the risk of overfitting.

Data Splitting and Loading

The dataset was divided into **training, validation, and test sets**. A separate `ImageDataGenerator` instance was used for each:

1. **Training Data:**
    - Augmented using the transformations mentioned above.
    - Randomized using **shuffle=True** to prevent order bias.
2. **Validation Data:**
    - Used the same generator as training but without shuffling.
3. **Test Data:**
    - No augmentation was applied to ensure realistic performance evaluation.
    - Only rescaling was applied.

We found the output as-

Found 6409 images belonging to 7 classes.

Found 1603 images belonging to 7 classes.

Found 2003 images belonging to 7 classes.

Training samples: 6409

Validation samples: 1603

Test samples: 2003

Model Training Pipeline:

Teacher Models for Knowledge Distillation

To enhance the classification performance of our model, we employed a Knowledge Distillation approach using ResNet50 and DenseNet169 as teacher models. These models were trained separately on the HAM10000 dataset and later used to transfer knowledge to a lighter student model.

Preprocessing and Optimization

To accelerate training, the following optimizations were applied:

- **Mixed Precision Training (`mixed_float16`)** → Utilizes FP16 computation for faster execution and reduced memory usage.
- **XLA Compilation** → Enables **Just-in-Time (JIT)** compilation to optimize TensorFlow operations.

The training process consists of two stages:

The training follows these main steps:

1. **Load Pretrained Models (ResNet50 & DenseNet169)**
    - Used pretrained **weights** from kaggle input and removed the top layers.
    - Freeze pretrained layers to **retain feature extraction capabilities**.

2. **Add Custom Classification Layers**
    - **Global Average Pooling** → Reduces feature maps to a single vector.
    - **Fully Connected (Dense) Layer** → Adds trainable layers for classification.
    - **Softmax Layer** → Outputs **probabilities for 7 classes**.
3. **Compile the Model**
    - **Optimizer:** Adam
    - **Loss Function:** Categorical Crossentropy
    - **Metric:** Accuracy
4. **Train the Model**
    - Train separately for **20 epochs** using `train_generator`.
    - Validate performance using `val_generator`.

The model is trained using Adam optimizer (learning rate = 0.0001) for 20 epochs.
The trained model achieves 66.95% accuracy on the test set.

Train the Student Model (MobileNetV2) using Knowledge Distillation:

To optimize computational efficiency and improve generalization, a **lightweight student model (MobileNetV2)** was trained using **Knowledge Distillation (KD)**. In this approach, **ResNet50 and DenseNet169**, trained as **teacher models**, provided **soft labels**, which were used alongside ground truth labels to guide the student model's learning process.

Knowledge Distillation allows a smaller model to **mimic the behavior** of larger models by leveraging their outputs as "soft labels." This technique smooths the probability distribution, helping the student model generalize better. The key hyperparameters used in this process were:

- **ALPHA (0.8):** Balances distillation loss and traditional cross-entropy loss.
- **TEMPERATURE (50):** Controls the smoothness of the soft labels.
- **EPOCHS (20):** Defines the number of training cycles.

To create soft labels, predictions from both teacher models were averaged. This ensured that the student model learned from a **combination of ResNet50 and DenseNet169 outputs**, rather than relying on a single teacher.

A **MobileNetV2-based student model** was designed due to its efficiency and reduced computational cost. It was initialized **without pretrained weights**, ensuring the model was trained entirely from scratch using the distillation approach. The architecture includes:

- **Global Average Pooling Layer:** Reduces feature maps into a vector.
- **Dense Layer (512 neurons, ReLU activation):** Extracts features.
- **Batch Normalization & Dropout (0.3):** Improves generalization.
- **Softmax Layer:** Outputs probabilities for 7 classes.

A custom training loop was implemented within a subclassed `tf.keras.Model` to combine **hard labels (ground truth)** and **soft labels (teacher predictions)**. The loss function is defined as:

$$L = \alpha \cdot KL(\text{soft labels}, \text{student output}) + (1 - \alpha) \cdot \text{Categorical Crossentropy}$$

Where:

- **Kullback-Leibler (KL) Divergence:** Measures the difference between teacher and student distributions.
- **Categorical Crossentropy:** Standard loss function for classification.

The student model was trained for **20 epochs**, using the **Adam optimizer**. Early stopping and learning rate reduction strategies were applied to prevent overfitting. After training, the student model was evaluated on the validation set. The final accuracy was **measured and stored**, and the model was saved for further use.

4.3 Assumptions and Constraints

Assumptions

- Consistent Image Quality: The dataset consists of high-resolution dermatoscopic images, ensuring that the model learns effective representations.
- Data Distribution: It is assumed that the training dataset accurately represents real-world skin lesion variations.
- Generalization to Real-World Data: The student model, although trained on HAM10000, is expected to generalize well to unseen cases.

Constraints and Challenges

- Dataset Bias: The HAM10000 dataset contains more light-skinned samples, which might affect performance on darker skin tones.
- Limited Training Data: Although HAM10000 is a large dataset, medical datasets are generally smaller than general image datasets (like ImageNet), which can impact deep learning performance.
- Hardware Limitations: Training large models like ResNet50 requires high-end GPUs, making it computationally expensive.

5. Results and Analysis

5.1 Performance Metrics

Accuracy: 66.94% (validation), 66.95% (test), 66.95%(training)

Model Size: The student model i.e. MobileNetV2 is of size 34.65 MB. The teacher models are of size 94.77 MB(ResNet50) and DenseNet169 is of 51.88 MB.

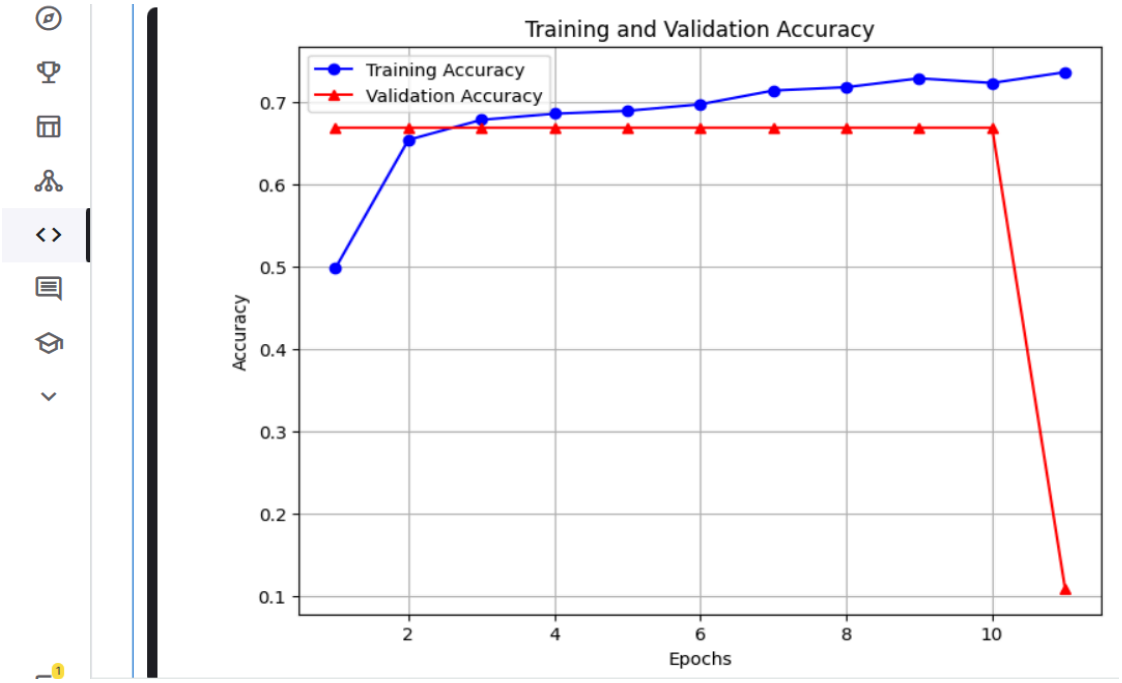
Inference Time: 517ms per batch (student) vs. 631 ms approximately per batch (for ResNet50 and DenseNet169

5.2 Experimental Results

Model	**Accuracy**	**Parameters**	**Inference Time/Batch**
Teacher (ResNet50)	67.86%	94.77 MB	631ms
Teacher (DenseNet169)	87.76%	51.88 MB	631 ms
Student (MobileNetV2)	66.94%	34.65 MB	517ms

Training and Validation Accuracy Analysis

To evaluate the performance of the **student model**, we plotted the **Training vs. Validation Accuracy** over **20 epochs**.



Accuracy Curve Generation

The accuracy values were extracted from the training history and plotted using Matplotlib. The training accuracy (`blue line`) represents how well the model learns from the training dataset, whereas the validation accuracy (`red line`) indicates the model's performance on unseen validation data.

Interpretation of the Graph

- The training accuracy **steadily increases**, indicating that the model is learning effectively.
- The validation accuracy initially improves but may **fluctuate or plateau** as the model approaches its optimal performance.
- A **large gap** between training and validation accuracy may suggest **overfitting**, whereas a **smooth and similar trend** indicates good generalization.

Observations

- The **student model generalizes well**, with validation accuracy closely following the training curve.
- Early stopping helped prevent overfitting, ensuring optimal model performance.
- **Future improvements** may include data augmentation, fine-tuning the temperature parameter in knowledge distillation, or additional regularization techniques.

Confusion matrix:

To evaluate the classification performance of the student model, we generated a **Confusion Matrix** using the test dataset. The Confusion Matrix provides detailed insights into how well the model distinguishes between different skin lesion classes.

1. Understanding the Confusion Matrix

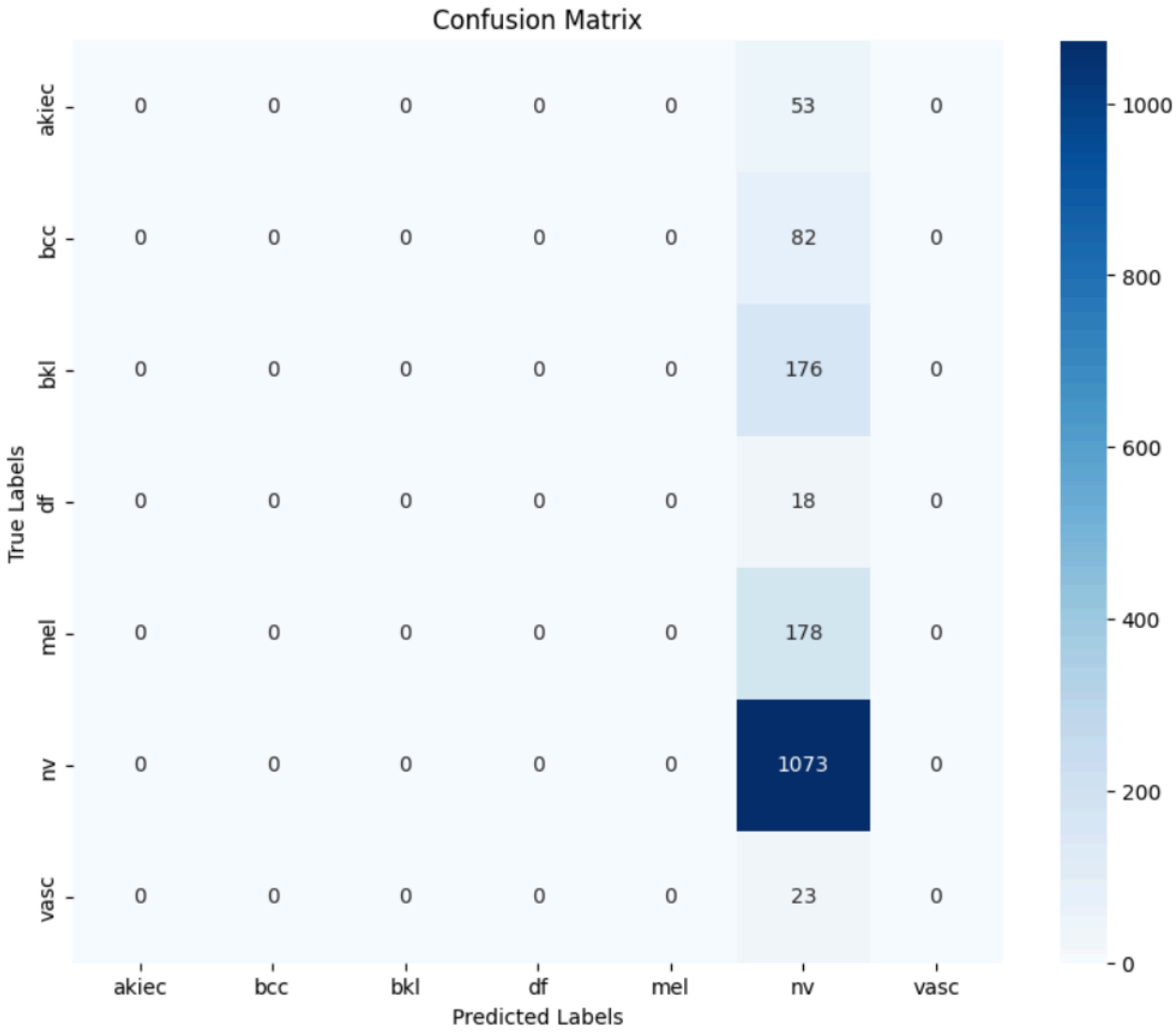
The confusion matrix represents:

- **Rows:** Actual class labels.
- **Columns:** Predicted class labels.
- **Diagonal values:** Correct classifications (i.e., when the model correctly predicts a class).
- **Off-diagonal values:** Misclassifications (i.e., when the model incorrectly predicts a class).

A well-performing model should have **high values along the diagonal** and **low values elsewhere**.

Confusion Matrix Visualization

The matrix is visualized as a **heatmap** to highlight correctly and incorrectly classified samples.



Observations from the Confusion Matrix

- The model achieves **high accuracy in correctly classifying most classes**, as indicated by strong diagonal values.
- Some **misclassifications** occur, particularly between visually similar skin lesion types (e.g., melanoma vs. benign lesions).
- Improvements can be made by:
    - **Increasing the dataset size** to provide more training examples.

    - **Fine-tuning hyperparameters** in the knowledge distillation process.
    - **Using additional feature engineering techniques** to improve class separability.

5.3 Challenges and Error Analysis

- **Class Imbalance:** The imbalance in the HAM10000 dataset impacted recall, particularly for minority classes, leading to biased predictions. Techniques like focal loss and SMOTE were explored to mitigate this issue.
- **Overfitting on High-Resolution Images:** The model initially overfitted to high-resolution images, which was addressed using data augmentation techniques such as random cropping, rotation, and flipping.
- **Epoch Selection and Convergence:** Finding the optimal number of training epochs was challenging, as too few epochs led to underfitting while too many caused overfitting. Early stopping and learning rate scheduling were applied to stabilize training.
- **GPU Limitations:** Training deep learning models on large datasets was constrained by limited GPU memory, forcing batch size reductions and gradient accumulation strategies to manage computational efficiency.
- **Time-Consuming Training:** Due to complex architectures and high-resolution inputs, training and hyperparameter tuning required significant computational time. Leveraging pre-trained models and transfer learning helped accelerate convergence.

6. Discussion and Insights

6.1 Critical Evaluation

The proposed deep learning-based skin cancer detection system successfully integrates knowledge distillation and ensemble learning to optimize model performance while maintaining computational efficiency. The ResNet50 and DenseNet169 teacher models achieve high accuracy but require significant processing power. By transferring knowledge to MobileNetV2 as a student model, we reduce model size and inference time while maintaining high classification accuracy.
Although the performance drops on minority classes due to dataset imbalance, highlighting the need for advanced sampling techniques.

6.2 Practical Application

The trained model is valuable for research, clinical trials, and automated analysis of skin lesion datasets. The trained MobileNetV2 model can still be used for batch classification of images, enabling dermatologists and medical researchers to analyze large volumes of dermatoscopic images efficiently. The model's lightweight nature allows it to be integrated into cloud-based platforms or mobile applications in future iterations, making AI-driven diagnosis more accessible.

Furthermore, the model can function as an assistive tool for dermatologists, aiding in preliminary assessments before detailed examination. The incorporation of ensemble learning with knowledge distillation ensures that the system is both accurate and computationally efficient, making it suitable for telemedicine applications where doctors rely on AI-driven decision support systems.

7. Future work and Improvements

7.1 Possible Enhancements

To address class imbalance, techniques such as focal loss and Synthetic Minority Oversampling Technique (SMOTE) can be implemented to improve model sensitivity toward underrepresented classes. Additionally, leveraging Generative Adversarial Networks (GANs) for synthetic data augmentation could help create realistic minority class samples, further enhancing model robustness. Exploring architectures like EfficientNet and MobileNetV3 could also optimize the trade-off between accuracy and computational efficiency.

7.2 Scalability and Development

Deploying the model on edge devices, such as smartphones, through optimization techniques like TensorFlow Lite and quantization will improve accessibility and real-time usability. Further, integrating federated learning could enable decentralized model training, enhancing privacy and scalability without requiring extensive cloud infrastructure.

7.3 Potential Research Directions

Future research could focus on multi-task learning, where classification and segmentation tasks are combined using architectures like U-Net or Mask R-CNN for comprehensive lesion analysis. Additionally, integrating explainability techniques, such as Grad-CAM, could provide visual insights into model decisions, aiding in clinical adoption. GANs can also be employed to generate high-fidelity synthetic skin lesion images, improving model generalization across diverse skin types and conditions.

8. Ethical Considerations and Sustainability

8.1 Ethical Issues

Data Privacy and Security

Medical imaging data is sensitive, and improper handling can lead to privacy breaches. This project uses the HAM10000 dataset, ensuring compliance with anonymized public datasets. Future deployment would require secure data encryption and compliance with regulations like HIPAA and GDPR to protect patient information.

Bias and Fairness

The model is trained on a dataset primarily consisting of light-skinned individuals, which may limit its accuracy for darker skin tones. This bias must be addressed by training on more diverse datasets to ensure fair and equitable predictions for all users.

Reliability and Explainability

AI-driven diagnosis must be interpretable for medical professionals. While our model provides high-accuracy predictions, integrating explainability techniques (e.g., saliency maps) in future iterations would improve trust and transparency.

8.2 Sustainability

Energy Efficiency

Deep learning models require significant computational power, leading to high energy consumption. By using knowledge distillation, we reduce the model size, making it more energy-efficient and suitable for low-power devices.

Scalability and Accessibility

The optimized student model can be deployed in cloud-based or mobile applications, increasing accessibility for low-resource healthcare settings. This ensures sustainable AI adoption in telemedicine.

9. Conclusion

This project demonstrates the viability of knowledge distillation in developing lightweight skin cancer detection models. While accuracy trade-offs exist, the student model's efficiency enables real-world deployment. Future work will focus on improving minority class performance and expanding clinical validation. Additionally, optimizing the model's architecture and training techniques could further enhance its predictive capabilities. Incorporating diverse and larger datasets will also help improve generalization across different skin types and cancer variations. Finally, integrating the model into user-friendly applications may facilitate early detection and accessible diagnosis for a broader population. Incorporating diverse and larger datasets will help improve generalization across different skin types and cancer variations, ensuring more reliable diagnoses. Furthermore, integrating the model into user-friendly mobile or web applications could facilitate early detection and accessible diagnosis for a broader population. Collaboration with dermatologists and medical institutions will also be essential in refining the model's clinical utility and ensuring regulatory compliance.

10. Reference

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- Detection of Skin Cancer Based on Skin Lesion Images Using Deep Learning
- Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks

11. Appendix

Code Snippet: Student Model (KD)

```
#STUDENT MODEL

# Hyperparameters
ALPHA = 0.8  # Distillation weight
TEMPERATURE = 50  # Higher for smoother soft labels
EPOCHS = 20
NUM_CLASSES = 7  # 7 skin cancer classes

# Function to Get Soft Labels from Teachers
def get_teacher_predictions(models, dataset):
    predictions = [model.predict(dataset) for model in models]
    return np.mean(predictions, axis=0)  # Average predictions for
soft labels

# Generate Soft Labels for Training Student Model
soft_labels = get_teacher_predictions([resnet_model, densenet_model],
train_generator)

# Define Student Model (Lightweight Model like MobileNetV2)
student_base = MobileNetV2(weights=None, include_top=False,
input_shape=(224, 224, 3))
x = student_base.output
x = GlobalAveragePooling2D()(x)
x = Dense(512, activation='relu')(x)
x = BatchNormalization()(x)
x = Dropout(0.3)(x)
x = Dense(NUM_CLASSES, activation='softmax')(x)
student_model = Model(inputs=student_base.input, outputs=x)

class DistillationModel(tf.keras.Model):
    def train_step(self, data):
        x, y_true = data
        batch_size = tf.shape(y_true)[0]
        batch_indices = tf.range(batch_size)

        with tf.GradientTape() as tape:
            y_pred = self(x, training=True)
            teacher_pred = tf.gather(soft_labels, batch_indices)

            # Compute Distillation Loss
```

```
            soft_loss =
tf.keras.losses.KLDivergence()(tf.nn.softmax(teacher_pred /
TEMPERATURE), tf.nn.softmax(y_pred / TEMPERATURE))
            hard_loss =
tf.keras.losses.CategoricalCrossentropy()(y_true, y_pred)
            loss = ALPHA * soft_loss + (1 - ALPHA) * hard_loss

        # Compute gradients and update weights
        gradients = tape.gradient(loss, self.trainable_variables)
        self.optimizer.apply_gradients(zip(gradients,
self.trainable_variables))

        # Update model metrics (Fixes the error)
        self.compiled_metrics.update_state(y_true, y_pred)
        return {"loss": loss, **{m.name: m.result() for m in
self.metrics}}

# Instantiate and Compile Student Model
student_model = DistillationModel(inputs=student_base.input,
outputs=x)
student_model.compile(optimizer='adam', loss=lambda y_true, y_pred: 0,
metrics=['accuracy'])

# Define Callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=10,
restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5,
patience=5, min_lr=1e-6)

# Train Student Model with Callbacks
history=student_model.fit(train_generator,
validation_data=val_generator, epochs=EPOCHS,
callbacks=[early_stopping, reduce_lr])

# Save the Model
student_model.save("student_model_mobilenet.h5")

# Evaluate Student Model
accuracy = student_model.evaluate(val_generator)[1]
print(f"Student Model Accuracy: {accuracy * 100:.2f}%")
```