MELANOMA CANCER DETECTION

Mini Project Report submitted by

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CERTIFICATE

Certified that the mini project work entitled

"Melanoma Cancer Prediction"

is a bonafide work carried out by

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It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated in the report.

The mini project report has been approved as it satisfies the academic requirements in respect of the mini project work prescribed for the Bachelor of Engineering Degree.

Signature of Guide **Signature of HOD**

Evaluation

Name of the Examiners	**Signature with Date**
1. ____________________	
2. ____________________	

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Abstract

Melanoma, a type of skin cancer, is characterized by the uncontrolled growth of melanocytes, the cells responsible for producing the pigment melanin. It is the most dangerous form of skin cancer due to its potential to metastasize or spread to other parts of the body. Deep learning, a subset of artificial intelligence, has emerged as a promising tool in the field of melanoma detection and diagnosis. By leveraging large datasets of skin images, deep learning algorithms can be trained to accurately identify and classify suspicious lesions. These algorithms can analyze various features of skin lesions, such as asymmetry, border irregularity, color variation, and diameter, aiding in the early detection of melanoma. Deep learning models have demonstrated impressive performance in distinguishing between benign and malignant skin lesions, assisting dermatologists in making more accurate diagnoses. The integration of deep learning into melanoma research and clinical practice holds great potential for improving outcomes and reducing mortality rates associated with this aggressive form of skin cancer.

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CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Early detection of melanoma, the deadliest form of skin cancer, is crucial for improving patient outcomes and reducing mortality rates. Traditional methods of melanoma diagnosis involve visual inspection and biopsy, which can be subjective and time-consuming. However, with recent advancements in deep learning, specifically Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs), there is a promising opportunity to enhance the early detection of melanoma. CNNs are deep learning architectures designed to process and analyze visual data, making them particularly suitable for image-based tasks such as melanoma detection. These networks consist of multiple layers of interconnected nodes that perform operations such as convolution, pooling, and non-linear activation. By leveraging large datasets of skin images, CNNs can learn complex patterns and features associated with melanoma, allowing them to automatically detect and classify suspicious lesions with high accuracy.

Additionally, ANNs, which are widely used in deep learning, can contribute to the early detection of melanoma. ANNs consist of interconnected artificial neurons organized in layers, with each neuron performing a weighted computation on its inputs and passing the result through an activation function. By training ANNs on diverse sets of clinical and patient data, including demographics, medical history, and genetic information, these networks can identify relevant patterns and risk factors associated with melanoma development.

The integration of CNNs and ANNs into melanoma detection systems holds great potential for revolutionizing the field. By leveraging the power of deep learning, these models can automate the analysis of skin images and patient data, providing dermatologists with invaluable assistance in identifying and diagnosing melanoma at its early stages. This can lead to timely interventions, personalized treatment plans, and improved patient outcomes.

1.2 PROBLEM STATEMENT

Melanoma, a highly malignant form of skin cancer, poses a significant health risk and has been on the rise in recent years. Early detection plays a crucial role in improving patient outcomes and reducing mortality rates. While visual inspection by dermatologists remains the gold standard for diagnosing melanoma, it can be subjective and prone to human error. There is a pressing need for an automated and reliable system that can assist in the early detection of melanoma using deep learning techniques. Existing computer-aided diagnostic systems for melanoma detection have shown promising results, but they still face several challenges. Firstly, the accuracy and robustness of these systems need to be further improved to ensure reliable detection across a wide range of skin types, lesion types, and imaging conditions. Secondly, the availability of high-quality labeled data for training deep learning models is limited, leading to difficulties in achieving optimal performance. Additionally, the interpretability and explainability of deep learning models for melanoma detection need to be addressed to build trust and confidence among clinicians. Therefore, the primary objective of this research is to develop an advanced deep learning-based system for the accurate and automated detection of melanoma. This system should overcome the limitations of existing approaches by addressing the challenges related to accuracy, robustness, data availability, and interpretability. By achieving this objective, it is anticipated that the proposed system will aid dermatologists in making timely and accurate diagnoses, leading to improved patient outcomes and a reduction in melanoma-related mortality rates.

1.3 OBJECTIVE

The objective of this research is to develop a deep learning-based system for the accurate and automated detection of melanoma. Enhance Accuracy and Robustness: Improve the system's accuracy by developing deep learning models that can effectively classify skin lesions and distinguish between benign and malignant cases. Overcome the limited availability of labeled data for training deep learning models by exploring techniques such as data augmentation, transfer learning, and semi-supervised learning. Optimize model performance despite the scarcity of labeled melanoma images.

1.4 MOTIVATION

Skin cancer is the most common type of cancer worldwide. Early detection and treatment of skin cancer can significantly improve the chances of successful treatment and reduce the risk of complications. In recent years, the use of artificial intelligence (AI) and machine learning (ML) algorithms has been gaining traction in the field of dermatology to aid in the early detection of skin cancer. Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that has shown great promise in the field of medical image analysis, including skin cancer detection. CNNs are designed to automatically learn and identify features from input images by using convolutional layers, which can help improve the accuracy of skin cancer detection. By training a CNN on a large dataset of images of both normal and cancerous skin, the model can learn to identify patterns and features that distinguish between the two. Once the model has been trained, it can be used to analyze new images and accurately predict whether or not a given skin lesion is cancerous. The motivation behind using CNNs for skin cancer detection is to improve the accuracy and efficiency of diagnosis. Traditional methods of diagnosing skin cancer rely on visual inspection by dermatologists, which can be time-consuming and may result in misdiagnosis or missed diagnoses. By leveraging the power of AI and machine learning, dermatologists can potentially make more accurate diagnoses in a shorter amount of time, leading to better outcomes for patients.

1.5 ORGANIZATION OF THE CHAPTERS

The project report has been organized under nine chapters, which are as follows:

Chapter I: Introduces to the main idea of the project. It gives a brief knowledge about the aim and methodology of the same.

Chapter II: It includes literature survey of related works.

Chapter III: Discusses the system requirements that are needed for the project. These include functional requirements, non-functional requirements, user requirements and hardware requirements.

Chapter IV: Includes the software approach.

Chapter V: Includes system Design like architecture and construction.

Chapter VI: Includes the implementation details of the project, application is explained in detail. It also deals with software approach.

Chapter VII: Outlines conclusions and future work that can be done.

CHAPTER 2
LITERATURE SURVEY

2.1 EXISTING METHOD

Several studies have explored the application of deep learning techniques for the detection of melanoma, leveraging advancements in image analysis and pattern recognition.
Deep Neural Networks (DNNs): DNNs have been widely used for melanoma detection. Studies have employed architectures such as convolutional neural networks (CNNs) to automatically extract relevant features from skin lesion images. These models are trained on large datasets of labeled images to learn discriminative patterns and classify lesions as either benign or malignant.

Transfer Learning: Transfer learning has been applied to overcome the limited availability of labeled melanoma images. Pre-trained CNN models, such as VGGNet and InceptionNet, trained on large-scale datasets like ImageNet, are fine-tuned on smaller melanoma datasets. This approach allows the models to leverage the learned features from the large dataset and adapt them to the melanoma detection task.

2.2 PROPOSED METHOD

Data Augmentation: Data augmentation techniques, such as rotation, scaling, and flipping, have been employed to artificially increase the diversity of the training dataset. By applying these transformations to existing melanoma images, the models can generalize better and improve performance.

Transformers: Transformers have emerged as a powerful deep learning architecture with potential applications in melanoma detection. Transformers excel at capturing long-range dependencies in data, making them suitable for analyzing high-resolution skin lesion images and capturing intricate patterns indicative of melanoma.
Transformers can effectively handle variable-sized input images, accommodating the diverse sizes and shapes of skin lesions encountered in melanoma detection.

CHAPTER 3
SYSTEM ANALYSIS AND REQUIREMENTS

3.1 SYSTEM AND REQUIREMENT ANALSIS

Skin cancer detection using a CNN system analysis is a powerful tool that utilizes deep learning algorithms to detect skin lesions that may indicate the presence of cancerous cells. In this report, we will discuss the process of skin cancer detection using a CNN system analysis, including the data collection and preprocessing, model architecture, and evaluation metrics.

Data Collection and Preprocessing: The first step in skin cancer detection using a CNN system analysis is to collect and preprocess the data. This involves gathering a dataset of images of skin lesions and labeling them as either benign or malignant. The dataset can be collected from various sources, such as public databases or medical institutions. Once the dataset is collected, the images must be preprocessed to improve the accuracy of the CNN system analysis. Preprocessing techniques include image resizing, normalization, and data augmentation. Image resizing ensures that all images are of the same size, while normalization adjusts the pixel values to a standardized scale. Data augmentation involves creating new images by rotating, flipping, or changing the brightness and contrast of existing images, which can help to increase the size of the dataset and improve the model's ability to generalize.

Model Architecture: The next step is to define the CNN model architecture. A common approach is to use a pre-trained model such as VGG16, ResNet, or Inception, which have been trained on large datasets such as ImageNet. These models can be fine-tuned by replacing the final fully connected layers with new layers that are specific to the skin cancer detection task. The CNN model typically consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers perform feature extraction by applying filters to the input images, while pooling layers reduce the dimensionality of the feature maps. Fully connected layers perform classification by mapping the extracted features to the output classes.

Evaluation Metrics: The final step is to evaluate the performance of the CNN system analysis. Common evaluation metrics for binary classification tasks include accuracy, precision, recall, and F1- score. Accuracy measures the percentage of correct predictions, while precision measures the proportion of true positives among the predicted positives. Recall measures the proportion of true positives among the actual positives, while F1-score is the harmonic mean of precision and recall.

3.2 FUNCTIONAL REQUIREMENT

Software Requirements:

Software: Jupyter Notebook.

Hardware Requirements:

Operating system: windows 7 and above.

RAM: 4GB and above.

Processor: Intel® Core(TM)2 duo CPU T6500.

Processor speed: 2.67 GHz.

CPU: 64-bit operating system.

3.3 NON-FUNCTIONAL REQUIREMENT

Nonfunctional Requirements (NFRs) define system attributes such as security, reliability, performance, maintainability, scalability, and usability. They serve as constraints or restrictions on the design of the system across the different backlogs. Also known as system qualities, nonfunctional requirements are just as critical as functional Epics, Capabilities, Features, and Stories. They ensure the usability and effectiveness of the entire system. Failing to meet any one of them can result in systems that fail to satisfy internal business, user, or market needs, or that do not fulfill mandatory requirements imposed by regulatory or standards agencies. In some cases, non-compliance can cause significant legal issues (privacy, security, safety, to name a few).

CHAPTER 4
SOFTWARE APPROACH

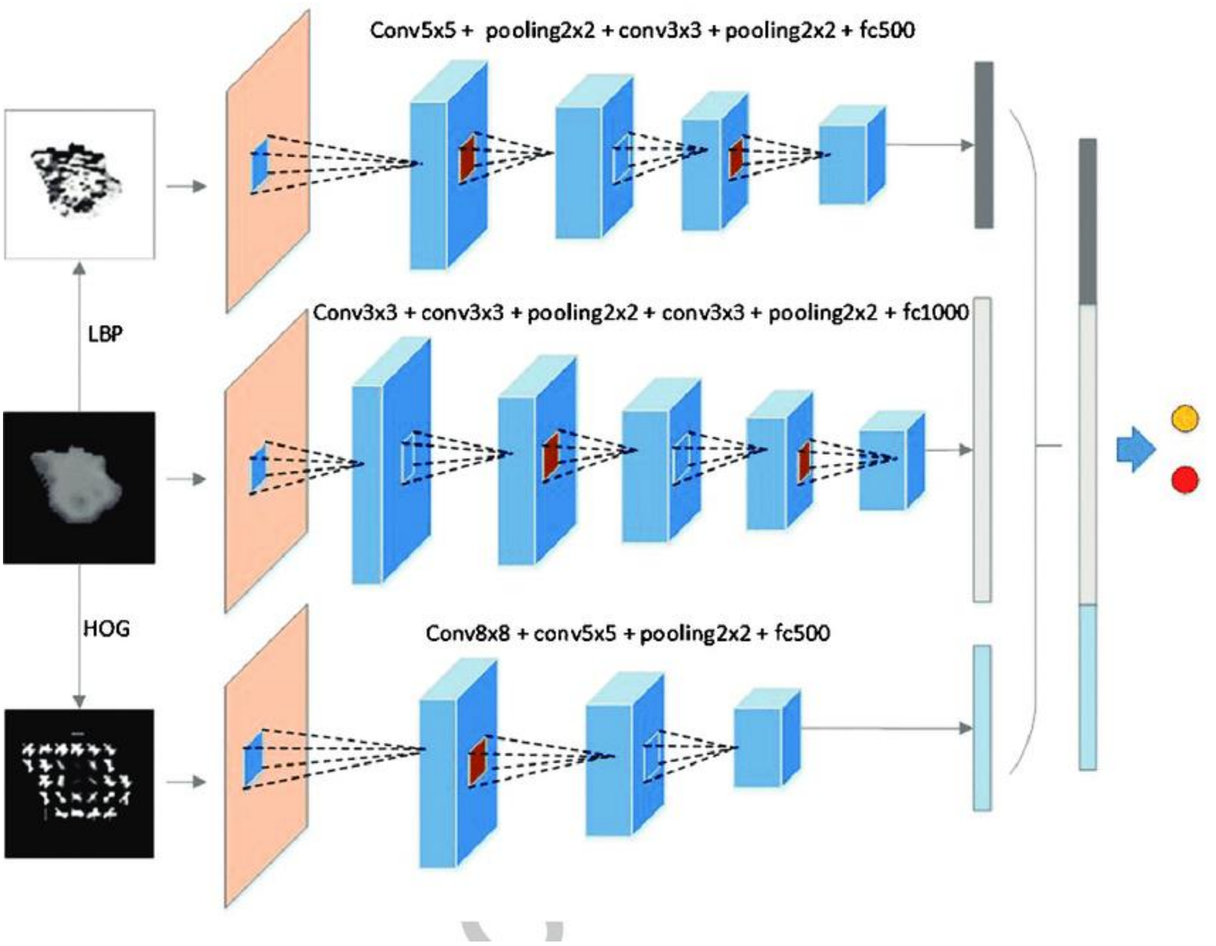
4.1 JUPYTER NOTEBOOK

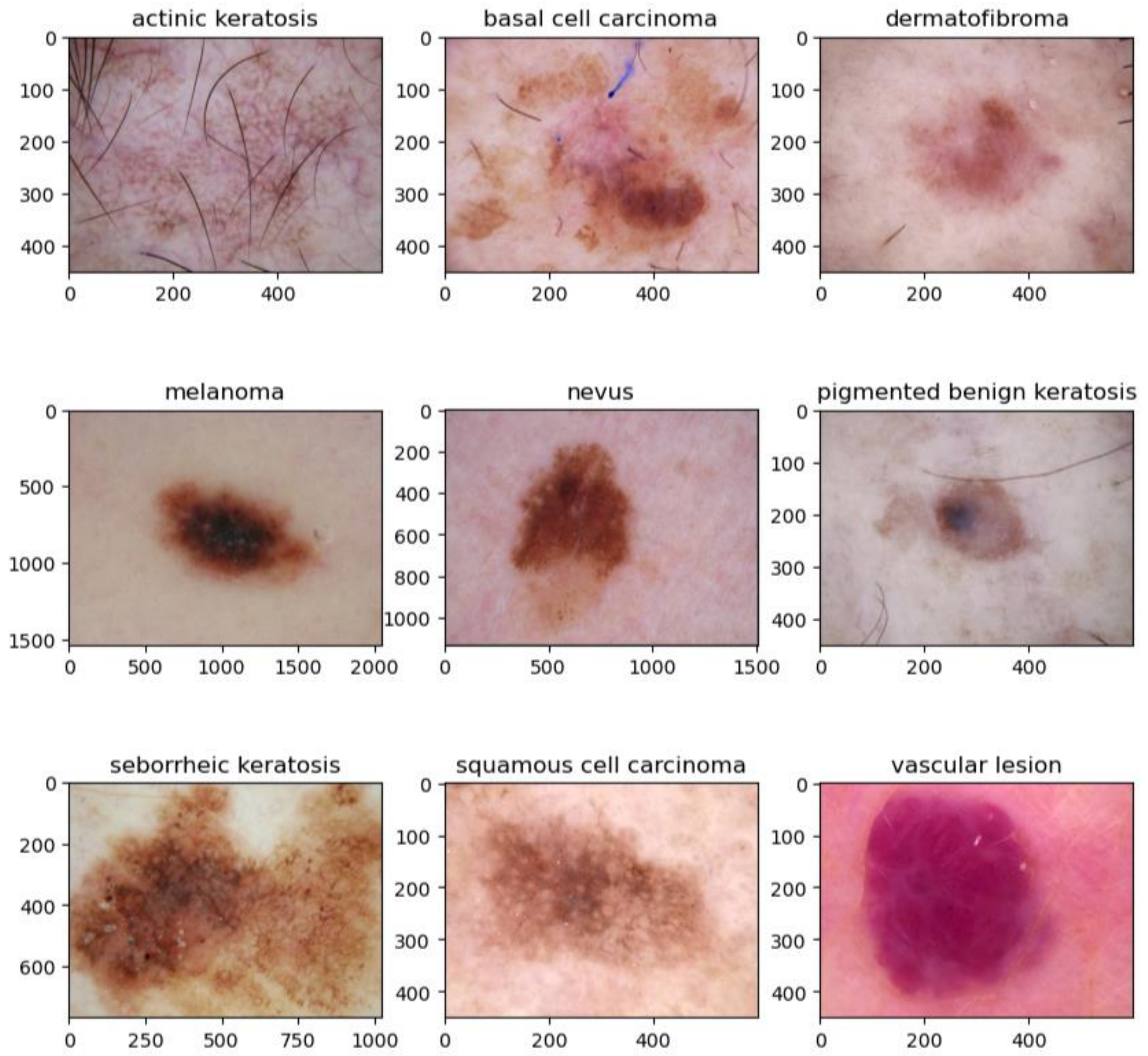
Jupyter Notebook is an interactive computing environment widely used for data analysis, scientific research, and development tasks. It provides a web-based interface that combines code, documentation, and visualizations in a single platform. Jupyter Notebook supports multiple programming languages, including Python, R, and Julia, allowing users to write and execute code cells interactively. These cells can be executed individually or in a specific order, providing a flexible and iterative workflow. Jupyter Notebook promotes reproducibility by allowing users to document their analysis, experiments, and findings alongside the code, facilitating collaboration and sharing of research or data analysis workflows. With its intuitive interface, rich display capabilities, and the ability to include equations, images, and interactive visualizations, Jupyter Notebook has become a popular tool for data scientists, researchers, and educators seeking an interactive and versatile environment for their computational work.

CHAPTER 5
SYSTEM IMPLIMENTATION

5.1 DESIGN SYSTEM

Firstly, the CNN model is designed for the system with the hidden layers. Later the transformers layers are added since CNN model demands high quality dataset and data, thus we use transformers concept so that low quality data can be used along with high quality data. Data augmentation is also used to enhance the accuracy of the system by flipping, rotating, zooming, re-sizing, shearing and by widening and increasing the height of the images in data.





Data augmentation:

Data augmentation is a technique commonly used in deep learning to artificially increase the size and diversity of a training dataset. By applying various transformations or modifications to the original data, data augmentation aims to create additional training examples that are similar to the original samples but exhibit variations. This augmentation process helps improve the generalization capability of deep learning models by exposing them to a wider range of data variations and reducing overfitting. Application of Augmentation Parameters: Augmentation parameters, such as rotation angles, scaling factors, or color shifts, are randomly generated within specified ranges. This randomness introduces diversity in the augmented examples.

```
In [46]: #Model 2 : Data Augumentation with drop out layer.
data_augmentation = keras.Sequential(
  [
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical",
                                                 input_shape=(img_height,
                                                              img_width,
                                                              3)),
    layers.experimental.preprocessing.RandomRotation(0.2),
    layers.experimental.preprocessing.RandomZoom(0.2),
  ]
)
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")

num_classes = 9
model = Sequential(data_augmentation)
model.add(layers.experimental.preprocessing.Rescaling(1.0/255,input_shape=(img_height,img_width,3)))

model.add(Conv2D(32, 3,padding="same",activation='relu'))
model.add(MaxPool2D())

model.add(Conv2D(64, 3,padding="same",activation='relu'))
model.add(MaxPool2D())

model.add(Conv2D(128, 3,padding="same",activation='relu'))
model.add(MaxPool2D())
model.add(Dropout(0.15))

model.add(Conv2D(256, 3,padding="same",activation='relu'))
model.add(MaxPool2D())
model.add(Dropout(0.20))

model.add(Conv2D(512, 3,padding="same",activation='relu'))
model.add(MaxPool2D())
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(1024,activation="relu"))
model.add(Dense(units=num_classes, activation= 'softmax'))
opt = Adam(lr=0.001)
model.compile(optimizer=opt,
              loss= SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])
```

Transformers:

Transformers can effectively capture spatial dependencies in high-resolution skin lesion images, enabling them to extract intricate patterns associated with melanoma. Transformers can be used to convert images into meaningful and compact representations by leveraging self-attention mechanisms and encoding image features. The self-attention mechanism in transformers can also aid in the accurate localization of melanoma within a skin lesion.

jupyter project ui Last Checkpoint: 17 minutes ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3 (ipykernel)

Run Code

```
ng\Python\Python39\Scripts' which is not on PATH.
  Consider adding this directory to PATH or, if you prefer to suppress this warning, use --no-warn-script-location.
```

In [6]:

```python
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import models
from torch.utils.data import DataLoader
from torchvision import transforms, datasets

# Define the path to the dataset
data_path = "Desktop/megh/Skin cancer ISIC The International Skin Imaging Collaboration/"

# Define the transformations to apply to the images
transform = transforms.Compose([
    transforms.Resize(224),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
])

# Load the dataset
dataset = datasets.ImageFolder(root=data_path, transform=transform)

# Split the dataset into training and validation sets
train_dataset, val_dataset = torch.utils.data.random_split(dataset, [int(len(dataset)*0.8), len(dataset)-int(len(dataset)*0.8)])

# Define the data loaders
batch_size = 32
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)

# Load a pre-trained ResNet-50 model
model = models.resnet50(pretrained=True)

# Replace the last fully-connected layer with a new one that has 2 output classes (melanoma and nevus)
num_ftrs = model.fc.in_features
model.fc = nn.Linear(num_ftrs, 2)

# Define the loss function and optimizer
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

# Train the model
num_epochs = 10
for epoch in range(num_epochs):
    train_loss = 0.0
    train_correct = 0.0
    for inputs, labels in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        train_loss += loss.item() * inputs.size(0)
        _, preds = torch.max(outputs, 1)
        train_correct += torch.sum(preds == labels.data)
    train_loss = train_loss / len(train_loader.dataset)
    train_acc = train_correct.double() / len(train_loader.dataset)

    # Evaluate the model on the validation set
    val_loss = 0.0
    val_correct = 0.0
    model.eval()
    with torch.no_grad():
        for inputs, labels in val_loader:
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            val_loss += loss.item() * inputs.size(0)
            _, preds = torch.max(outputs, 1)
            val_correct += torch.sum(preds == labels.data)
    val_loss = val_loss / len(val_loader.dataset)
    val_acc = val_correct.double() / len(val_loader.dataset)

    # Print the loss and accuracy for this epoch
    print('Epoch [{}/{}], Train Loss: {:.4f}, Train Acc: {:.4f}, Val Loss: {:.4f}, Val Acc: {:.4f}'
          .format(epoch+1, num_epochs, train_loss, train_acc, val_loss, val_acc))

# Compute the overall accuracy on the test set
test_dataset = datasets.ImageFolder(root=data_path + "/test", transform=transform)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)
```

CHAPTER 6
SYSTEM TESTING

6.1 TESTING

The final trained model is evaluated on an independent testing dataset, which contains skin lesion images not seen during training or validation. The model predicts the classification (benign or malignant) for each image, and the results are compared with ground truth labels to measure its accuracy, sensitivity, specificity, and other performance metrics. The trained model is evaluated on a separate validation dataset to assess its performance and tune its hyperparameters. This step helps ensure that the model generalizes well to unseen data and avoids overfitting.

CHAPTER 7
WORKING

7.1 RESULTS

Accuracy of the model went on increasing as the number of epochs were increased along with introduction of new hidden layers, data augmentation, transformers, thus providing the CNN model with a total up to 80%+ accuracy in predicting the Melanoma skin cancer. Once the model has achieved satisfactory performance, it can be deployed and integrated into clinical workflows. Dermatologists and healthcare professionals can use the model as an aid in the early detection and diagnosis of melanoma, leveraging its ability to analyze skin lesion images and provide predictions.

CHAPTER 8
CONCLUSION AND FUTURE WORK

8.1 CONCLUSION

In conclusion, the application of deep learning techniques, such as convolutional neural networks (CNNs) and transformers, has shown great promise in the detection of melanoma. These techniques enable the automated analysis of skin lesion images, providing valuable support to dermatologists in making accurate and timely diagnoses.

By leveraging deep learning models, clinicians can benefit from enhanced accuracy, improved localization, and reliable predictions for melanoma detection. The models excel at capturing intricate patterns, handling variable-sized images, and exploiting self-attention mechanisms to focus on relevant features. Additionally, the interpretability of deep learning models allows clinicians to understand the reasoning behind the model's predictions, fostering trust and facilitating informed decision-making.

Data augmentation techniques play a vital role in training robust deep learning models by artificially expanding the training dataset and increasing its diversity. This addresses the challenge of limited labeled data for melanoma detection and improves the model's generalization capability.

8.2 FUTURE WORK

The integration of deep learning models into clinical workflows has the potential to revolutionize melanoma detection by providing efficient and accurate screening tools. However, it is important to consider the limitations of the current models, such as the need for large, diverse, and well-curated datasets, as well as ongoing research to optimize and fine-tune these models for better performance.

Currently, most CNN models focus on dermoscopic images alone. Integrating other modalities, such as clinical data, patient history, or additional imaging techniques (e.g., confocal microscopy), could provide complementary information for improved diagnosis and decision-making.

In the future, continued advancements in deep learning, along with collaborations between researchers, clinicians, and industry experts, will contribute to further improving the accuracy, efficiency, and reliability of melanoma detection models. By harnessing the power of deep learning, we can strive towards early and accurate diagnoses, leading to improved patient outcomes and ultimately combating melanoma, a potentially life-threatening form of skin cancer.

CHAPTER 9
REFERENCES

9.1 REFERENCES

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