Department of Electrical and Computer Engineering
North South University

Senior Design Project

Image Classification and Analysis of Arsenicosis affected skin of Bangladeshi people using deep learning

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Summer, 2024

LETTER OF TRANSMITTAL

November, 2024

To

Dr. Mohammad Abdul Matin
Chairman
Department of Electrical and Computer Engineering
North South University, Dhaka

Subject: **Submission of Capstone Project Report on "Image Classification and Analysis of Arsenicosis affected Skin of Bangladeshi People using Deep Learning"**

Dear Sir,
With due respect, we would like to submit our **Capstone Project Report** on **"Image Classification and Analysis of Arsenicosis affected Skin of Bangladeshi People using Deep Learning"** as a part of our BSc program. It focuses on using deep learning techniques to analyze images of skin affected by arsenicosis in Bangladesh. The goal is to aid in early detection and diagnosis of arsenicosis, which is a significant health issue in Bangladesh due to contaminated groundwater. This project will help us gain experience from the practical field and apply in real life. We will try to maximize competence to meet all the dimensions required from this report.

We will be highly obliged if you kindly receive this report and provide your valuable judgment. It would be our immense pleasure if you find this report useful and informative to have an apparent perspective on the issue.

Sincerely Yours,

....
Tamanna Rahman
ECE Department
North South University, Bangladesh

....
Anika Hossain
ECE Department
North South University, Bangladesh

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APPROVAL

Tamanna Rahman (#2021450642), Anika Hossain (#2111687642) and Sabbir Mehtaj (#2013438042) from Electrical and Computer Engineering Department of North South University, have worked on the Senior Design Project titled **“Image Classification and Analysis of Arsenicosis affected skin of Bangladeshi people using deep learning”** under the supervision of Dr. Mohammad Ashrafuzzaman Khan partial fulfillment of the requirement for the degree of Bachelors of Science in Engineering and has been accepted as satisfactory.

Supervisor’s Signature

……………………………………….

Dr. Mohammad Ashrafuzzaman Khan

Associate Professor

Department of Electrical and Computer Engineering

North South University

Dhaka, Bangladesh.

Chairman’s Signature

……………………………………….

Dr. Mohammad Abdul Matin

Professor

Department of Electrical and Computer Engineering

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Dhaka, Bangladesh.

DECLARATION

This is to declare that this project is our original work. No part of this work has been submitted elsewhere partially or fully for the award of any other degree or diploma. All project related information will remain confidential and shall not be disclosed without the formal consent of the project supervisor. Relevant previous works presented in this report have been properly acknowledged and cited. The plagiarism policy, as stated by the supervisor, has been maintained.

Students' names & Signatures

1. Tamanna Rahman

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2. Anika Hossain

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3. Sabbir Mehtaj

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ABSTRACT

Image Classification and Analysis of Arsenicosis affected Skin of Bangladeshi People using Deep Learning

In Bangladesh, arsenicosis, a severe skin disease caused by chronic arsenic poisoning, is a significant health issue due to the widespread presence of arsenic in drinking water. The conventional diagnostic methods for arsenicosis, which are quite tricky and require an expert in dermatology, become impractical if not properly trained in remote areas. The paper intends to offer computerized ways for detecting and classifying the Arsenicosis-affected skin using newly invented deep learning techniques. We have built and controlled a multitude of convolutional neural network models for identifying skin images collected from Bangladeshi patients. The models were built on a heterogeneous database with healthy as well as Arsenicosis-affected skin images in order to create a robust and accurate diagnostic tool. Our diagnosis with supervised models such as: MobileNet V3 Large, EfficientNet, MobileNet V2 has yielded a testing accuracy of 100% and a training accuracy of 99.53%, 99.80% and 99.63% and unsupervised models VIT b-16 and SimCLR has 99.61% and 100% accuracy on test set respectively.

TABLE OF CONTENTS

LETTER OF TRANSMITTAL 2

APPROVAL 4

DECLARATION 5

ACKNOWLEDGEMENTS 6

ABSTRACT 7

LIST OF FIGURES 10

LIST OF TABLES 11

Chapter 1 Introduction 12

1.1 Background and Motivation 12

1.2 Purpose and Goal of the Project 12

1.3 Organization of the Report 13

Chapter 2 Research Literature Review 14

2.1 Existing Research and Limitations 14

Chapter 3 Methodology 19

3.1 System Design 19

3.2 Hardware and/or Software Components 21

3.3 Hardware and/or Software Implementation 24

Chapter 4 Investigation/Experiment, Result, Analysis and Discussion 25

Chapter 5 Impacts of the Project 33

5.1 Impact of this project on societal, health, safety, legal and cultural issues 33

5.2 Impact of this project on environment and sustainability 35

Chapter 6 Project Planning and Budget 38

Chapter 7 Complex Engineering Problems and Activities 39

7.1 Complex Engineering Problems (CEP) 39

7.2 Complex Engineering Activities (CEA) 40
Chapter 8 Conclusions 41
8.1 Summary 41
8.2 Limitations 41
8.3 Future Improvement 42
References 42

LIST OF FIGURES

Figure 3.1: Block Diagram of Project Design 19
Figure 3.2: Dataset Sample 21
Figure 4.1: Classification Report for MobileNet V3 Large 29
Figure 4.2: Confusion Matrix for MobileNet V3 Large 30
Figure 4.3: Classification Report for EfficientNet 30
Figure 4.4: Confusion Matrix for EfficientNet 31
Figure 4.5: Classification Report for EfficientNet 31
Figure 4.6: Confusion Matrix for EfficientNet 32
Figure 6.1: Gantt chart of Project Planning 37
Figure 6.2: Project Budget Table 37

LIST OF TABLES

Table 1. List of Software Components 23

Table 2. Hyperparameters for Training an Original Dataset 25

Table 3. Model Results (Original Dataset) 26

Table 4. Hyperparameters for Training 26

Table 5. Model Results (Original and Augmented Dataset) 28

Table 6. Complex Engineering Problem Attributes 38

Table 7. Complex Engineering Problem Activities 39

Chapter 1 Introduction

1.1 Background and Motivation

Arsenicosis is a chronic health condition caused by long-term exposure to arsenic, a naturally occurring element found in groundwater and soil. Bangladesh faces a significant public health challenge due to widespread arsenic contamination in drinking water sources [1]. This contamination manifests in various skin lesions, including hyperpigmentation, keratosis, and potentially malignant growths [2]. Early diagnosis of arsenicosis is crucial for effective treatment and preventing future health complications. However, traditional diagnostic methods rely on invasive biopsies and specialist expertise, which can be limited in resource-constrained settings.This motivates the exploration of deep learning techniques for image classification and analysis of arsenicosis-affected skin. Deep learning has achieved remarkable success in medical image analysis tasks, offering the potential for a non-invasive, automated, and potentially point-of-care diagnostic tool.

1.2 Purpose and Goal of the Project

The primary purpose of this project is to develop a reliable and efficient image classification system capable of identifying arsenicosis-affected skin among individuals in Bangladesh. Prolonged exposure to water tainted with arsenic can induce arsenicosis, which is a serious health concern in many areas, including the district of Chapainawabganj. Effective treatment and avoiding serious complications depend on early detection. This project intends to improve the accuracy and timeliness of medical evaluations in resource-limited situations by facilitating the early identification of arsenicosis using automated image analysis by utilizing advanced deep learning techniques, specifically Convolutional Neural Networks (CNNs).

The goal of the project is to build a strong deep learning model that can accurately identify between skin that is healthy and skin that has arsenicosis. The study's dataset comprises a significant quantity of photographs gathered from four distinct villages, guaranteeing a varied portrayal of the impacted populace. The model's performance and generalization ability are further enhanced by adding to the original dataset. The ultimate goal of this project is to provide a useful tool that medical personnel may use to quickly diagnose cases of arsenicosis, improving patient outcomes and lessening the effects of arsenic poisoning in impacted populations.

1.3 Organization of the Report

The report will be organized as follows: **Chapter 1** will provide an introduction to arsenicosis and the motivation for using deep learning for image classification. **Chapter 2** will delve into existing research on arsenicosis skin image analysis and deep learning applications in dermatology. **Chapter 3** will detail the methodology, including the data collection process and the chosen deep learning architecture. **Chapter 4** will present the investigation's experiments, results, analysis, and discussion of the model's performance. **Chapter 5** will explore the ethical and professional responsibilities, environment and sustainability impacts of the project on healthcare and arsenic exposure detection. **Chapter 6** will outline the project plan and budget, while **Chapter 7** will address any complex engineering problems or activities encountered during development. Finally, **Chapter 8** will summarize the project's findings and offer concluding remarks.

Chapter 2 Research Literature Review

2.1 Existing Research and Limitations

Emu, Ismot Ara, et al. introduces the ArsenicSkinImageBD dataset [3], specifically crafted to facilitate the training of machine learning algorithms in identifying arsenicosis, a skin ailment linked to arsenic exposure. Addressing the inherent challenges in acquiring medical imagery, the authors navigate through privacy concerns and potential biases. They acknowledge potential issues like data imbalance stemming from participant self-selection and varying image qualities influenced by multiple factors.

However, the researchers meticulously curated the dataset, prioritizing ethical data procurement and image quality. By incorporating a diverse array of images showcasing healthy skin, arsenic-affected skin, and visually similar conditions, they aimed to bolster the model's discriminatory capabilities. This initiative marks a significant step forward in enabling further exploration into AI-driven diagnostic tools for arsenicosis detection.

Lindberg, Anna-Lena, et al. investigates the factors influencing the development of arsenic-induced skin lesions in Bangladesh [4]. The study confirms previous findings that men are more susceptible to these skin lesions compared to women. They delve deeper into the underlying reasons for this difference. Their analysis reveals that men exhibit less efficient arsenic metabolism. This means their bodies have difficulty converting the toxic inorganic arsenic into a less harmful form (dimethylarsinic acid - DMA) through a process called methylation. Instead, a higher proportion of inorganic arsenic remains unconverted and another intermediate metabolite (monomethylarsonic acid - MMA) accumulates. This difference in arsenic metabolism is linked to the observed higher risk of skin lesions in men.

Interestingly, the study also finds that individuals exposed to arsenic since infancy (or even before birth) have a lower risk of developing skin lesions irrespective of their gender or methylation efficiency. This suggests a potential protective effect from early life exposure, possibly due to adaptations in the body's response to arsenic.

Kadono, Takafumi, et al. addresses the widespread issue of arsenic contamination in Bangladesh, affecting millions through polluted groundwater [5]. While the study acknowledges the known impact, it highlights a crucial gap - understanding the true extent of the problem within communities. The researchers focus on the telltale signs of arsenic poisoning - skin manifestations. Examining over 500 individuals, the study revealed a significant portion (over 50%) exhibiting these markers. Notably, rough, thickened skin on the soles (keratosis) proved to be the most effective indicator for early detection. Interestingly, males displayed a higher severity of skin issues compared to females.

The findings underline a critical public health concern. The widespread presence of skin manifestations suggests a considerably high prevalence of arsenicosis. Early detection through markers like sole keratosis is crucial. The study emphasizes the urgent need for comprehensive assessments across Bangladesh to determine the exact scale of the problem and implement appropriate measures to manage and treat the affected population.

Karim, MD Masud highlights Bangladesh's pressing issue of arsenic contamination in groundwater, posing severe health risks to its population due to levels surpassing WHO safety standards [6]. This silent threat has led to widespread health issues, from cancer to reproductive problems. Mitigating arsenic pollution in tubewell water requires a multifaceted approach, including alternative water sources, treatment technologies, safe tubewells, monitoring, community engagement, and policy enforcement. Through concerted efforts in technology, public health initiatives, and ongoing research, Bangladesh can strive for a future where access to safe drinking water is ensured for all.

Demissie, Solomon, et al. focuses on skin lesions caused by arsenic exposure in Ethiopia, particularly in the Adami Tulu Jido Kombolcha district [7]. The study found a prevalence of arsenicosis at 2.2% among 403 participants, with keratosis being the most common type of skin lesion observed. Factors such as consuming contaminated water, cigarette smoking, and chewing khat were identified as significant contributors to arsenicosis. However, this study's scope is limited to a specific region, and further research is required to ascertain the overall prevalence of arsenic-induced skin lesions across Ethiopia.

Wang, Jason, and Luis Perez describes, data augmentation is an eventual technique in the realm of deep learning for image classification [8]. Its effectiveness stems from its ability to artificially expand the shape and diversity of training datasets. Data augmentation plays a vital introduction in enhancing the effectiveness of deep learning models for image classification by increasing dataset size, improving generalization, acting as regularization, addressing class imbalances, facilitating transfer learning, and reducing overfitting. It is a fundamental technique employed in training deep learning models for various computer vision tasks. We also experiment with GANs to generate images of different styles. Finally, we propose a method to allow a neural net to learn augmentations that best improve the classifier, which we call neural augmentation. We discuss the successes and shortcomings of this method on various datasets.

Rajiv, Shwetha V. delves into the widespread problem of arsenic toxicity, which poses significant health risks globally through various sources like natural occurrences, industries, and medicines [9]. It primarily affects the skin and nervous system, with skin changes often signaling early signs. Although international guidelines are lacking, the paper suggests diagnostic methods including histopathological, laboratory, and clinical criteria, with atomic absorption spectroscopy as the preferred method for detecting arsenic levels. Treatment options include chelating agents and other therapies, yet no definitive cure exists. Prevention strategies emphasize awareness and regular water testing, aiming to reduce exposure. The review aims to equip healthcare professionals, especially dermatologists, with crucial information to tackle arsenic toxicity effectively.

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton [10] offers the groundbreaking study under review describes the training of a large, deep convolutional neural network on 1.2 million high-resolution images from the ImageNet LSVRC-2010 contest, resulting in top-1 and top-5 error rates of 37.5% and 17.0%, respectively, outperforming previous state-of-the-art approaches. The neural network has 60 million parameters and 650,000 neurons, with a sophisticated architecture that includes five convolutional layers, some followed by max-pooling layers, and three fully-connected layers, culminating in a 1000-way softmax. To speed up training, the authors use non-saturating neurons and an efficient GPU implementation. Furthermore, they combat overfitting by strategically implementing dropout regularization. This unique approach is applied to the ILSVRC-2012 competition, where a variant of the model obtains a top-5 test error rate of 15.3%, significantly outperforming the second-best entry's performance of 26.2%. These findings demonstrate the efficacy of large-scale deep learning architectures and the necessity of efficient training procedures in pushing the frontiers of object identification performance, establishing a new standard in the field. Looking ahead, the scientists envisage further improvements through unsupervised pre-training and the use of very large and deep CNNs on video sequences, to mimic the inferotemporal route of the human visual system. This paper establishes a standard for object recognition using deep learning, emphasizing the role of dataset size, model complexity, and training strategies in obtaining remarkable performance.

Van Gansbeke, Wouter, et al. proposes a two-step approach to unsupervised image classification [11], departing from end-to-end methods. Initially, it employs self-supervised learning for feature extraction, emphasizing the importance of selecting a pretext task that yields semantically meaningful features. These features are then utilized as a prior in a novel clustering-based classification framework. The method addresses noise in nearest neighbor selection through self-labeling. Experimental results demonstrate significant performance improvements over state-of-the-art methods across various datasets, notably achieving a remarkable increase in accuracy on CIFAR10, CIFAR100-20, and STL10. Notably, it excels on ImageNet without ground-truth annotations, surpassing several semi-supervised learning techniques in low-data scenarios. The authors provide their code for public use. The study concludes by highlighting the advantages of their approach over end-to-end strategies, with promising implications for large-scale datasets like ImageNet. The authors express optimism about extending their framework to other domains such as semantic segmentation, semi-supervised learning, and few-shot learning. The research received support from Toyota through the TRACE project and MACCHINA, along with valuable insights from collaborators and peers. Overall, the paper introduces a robust framework for unsupervised image classification, showcasing significant advancements in performance and scalability, and paving the way for further applications in related areas of computer vision.

He et al. (2016) first proposed the Deep Residual Learning framework, and ResNet, commonly referred to as ResNet, was one of the methods that helped to change the way deep convolutional neural networks were used for the recognition of images. [12] The main novelty of this paper is the presentation of quality blocks made by the use of skip eventual apeacement connections that allow them to go across one or more layers, thus addressing the problem of diminishing gradients and at the same time making it possible to train very deep networks (He et al., 2016). The authors showed that the use of residual blocks has shown an immense improvement in the ImageNet classification task by reaching the top-5 error rate of 3.57%, which is a bit greater than the case of prior top-of-the-line models (He et al., 2016). This paper is the blueprint for the future development of deep learning architectures since it has been proven that deep networks can be quite efficient.

Limitations:

- While GradCAM was integrated into the project to enhance model explainability, its scope remains limited to highlighting important regions in input images. More advanced XAI techniques, such as SHAP or integrated gradients, could provide deeper insights into the decision-making process of the models. However, their implementation is constrained by computational requirements and time considerations.
- The training and evaluation of deep learning models required significant computational resources, which posed a limitation for this study. High-performance GPUs were essential to process the dataset efficiently and train complex models like EfficientNet and SimCLR. Limited access to such resources may restrict broader adoption of similar systems in resource-constrained settings.
- Although the models performed exceptionally well on the given dataset, their generalizability to new, unseen datasets or real-world scenarios remains untested. Variations in lighting, skin conditions, and image quality across different regions may impact performance, requiring further evaluation and fine-tuning.
- The project relied on a dataset of 1,482 original and 8,892 augmented images. The limited availability of high-quality, annotated data specific to arsenicosis presents a challenge for scaling and improving the system. Future work would benefit from collecting larger, diverse datasets to ensure the models' robustness and broader applicability.

Chapter 3 Methodology

3.1 System Design

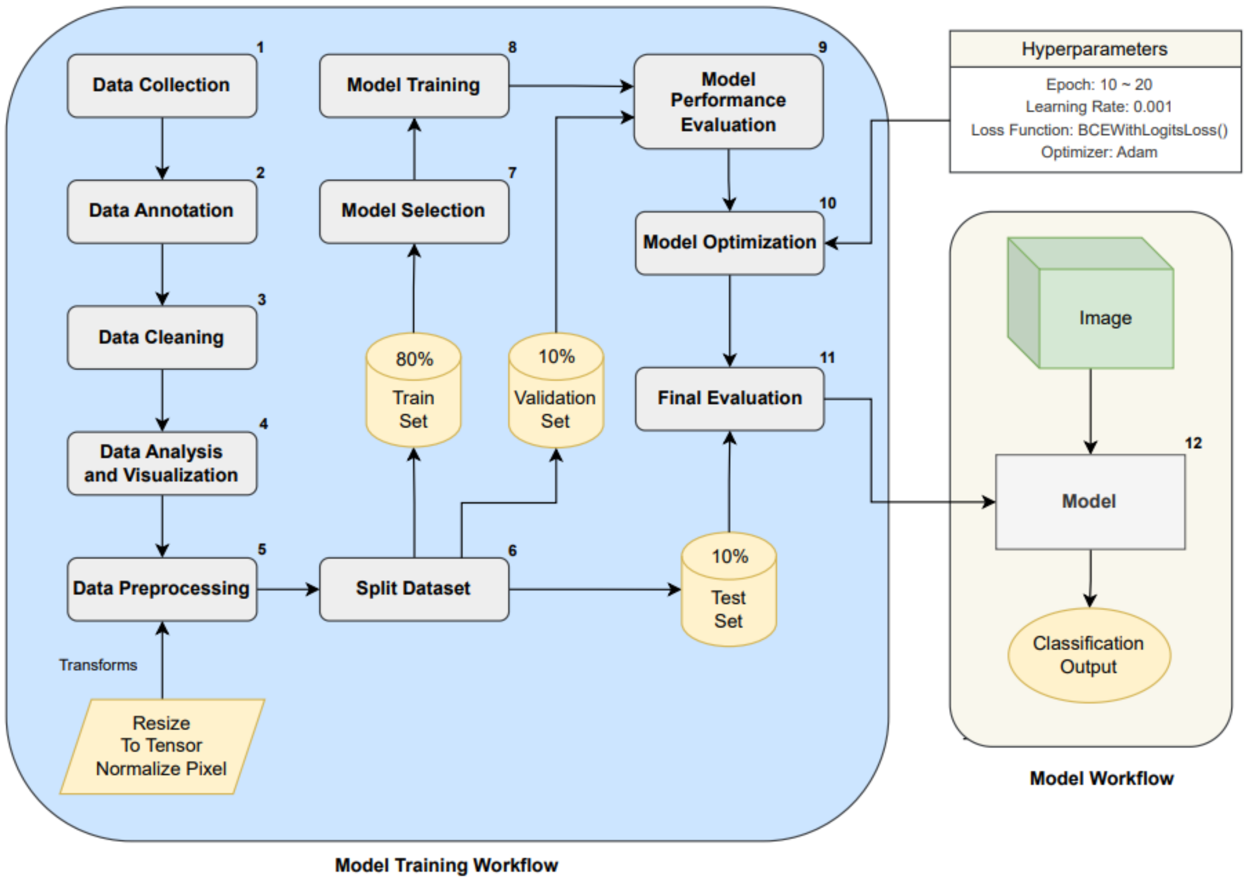

Figure 3.1: Block Diagram of Project Design

The system design consists of two main data sets: a training set and a test set. The training set is used to train a deep learning model to classify images into two categories: arsenicosis-affected skin and healthy skin. The test set is used to evaluate the performance of the trained model.

The system design can be broken down into the following steps:

Pre-process Images: This module refers to the process of preparing the training set images for training the deep learning model. Preprocessing may include resizing the images, converting them to a common format, and normalizing the pixel values.

Train Set: This is a reference to the set of photos that the deep learning model was trained on. The training set ought to be an accurate representation of the actual data that the model will analyze.

Test Set: This is a reference to an additional set of photos that are used to assess how well the trained model performs. The test set ought to be typical of the actual data that the model will be applied on.

Training on Pre-trained CNN Models: The deep learning model starts with a pre-trained convolutional neural network (CNN) model. One kind of artificial neural network that was created especially for image identification applications is the CNN model. With the help of a sizable image dataset, the pre-trained CNN model has already gained the ability to recognize low-level features like edges and lines in images.

Training on Unsupervised Model: For the unsupervised models, Vision Transformer (ViT) and SimCLR, the dataset was first preprocessed by resizing, normalizing, and applying augmentations to enhance feature diversity. SimCLR was trained using contrastive learning, where the model learned to differentiate between similar and dissimilar pairs of augmented images. ViT was pre-trained with self-supervised learning, leveraging the dataset's structure to understand image features without labeled data. Both models were fine-tuned on the labeled dataset, achieving high accuracy, with SimCLR demonstrating excellent performance for arsenicosis classification.

Evaluation: The test set is used to evaluate the model once it has been trained. A distinct collection of photos that the model has never seen before makes up the test set. The correctness of the model on the test set is measured as part of the evaluation procedure. This makes it easier to assess how effectively the model applies to new data.

Compare Train/Test Loss and Metrics: The technique of assessing the trained model's performance on the test set is discussed in this section. The correctness of the model on the test set is measured as part of the evaluation procedure. This makes it easier to assess how effectively the model applies to new data.

3.2 Software Components

The implementation of this project involved several key software components and methodologies to ensure the development of an accurate and robust image classification model for detecting arsenicosis-affected skin. These components include dataset handling, exploratory data analysis (EDA), preprocessing techniques, the application of deep learning models, and optimization methods.

Dataset

The dataset comprised a total of 1482 original images and 8892 augmented images, sourced from four villages in the Chapainawabganj district of Bangladesh. The images were categorized into two classes: healthy and arsenicosis-affected skin. For model training and evaluation, the dataset was split into a training set with 1030 images and a test set with 257 images.

a) Infacted **b) Not Infacted**

Figure 3.2: Dataset Sample

Exploratory Data Analysis (EDA)

EDA was used to get insights into the dataset, which included distribution analysis, class imbalance checks, and picture inspection. This stage helped to grasp the dataset's characteristics and informed further preprocessing steps.

Preprocessing Techniques

Preprocessing involved several steps to prepare the images for training:

- Resizing: All images were resized to a consistent dimension suitable for input into the CNN model.
- Normalization: Image pixel values were normalized to a range of [0, 1] to standardize the input data.
- Augmentation: Techniques such as rotation, flipping, and zooming were applied to the original images to create an augmented dataset, enhancing the model's ability to generalize.

Applied Deep Learning Model

A Convolutional Neural Network (CNN) was utilized for the image classification task. The architecture was designed to capture the intricate patterns in skin images that distinguish healthy skin from arsenicosis-affected skin. Key hyperparameters for the model training included:

Number of Epochs: 10~20

Batch Size: 32

Learning Rate: 0.001

Optimization Techniques

Faster convergence was achieved by using the Adam optimizer, which is renowned for its efficiency and flexible learning rate capabilities, in the training process. Because the classification job is binary in nature, the model's performance was measured using the binary cross-entropy loss function, or BCELoss.

Hyperparameter Optimization

To maximize the performance of the model, manual adjustments were made to hyperparameters such learning rate, batch size, and number of epochs. More advanced hyperparameter optimization methods, like grid search or random search, may be used in future studies to further optimize the process.

By integrating these software components and techniques, the project successfully developed a CNN-based model capable of accurately classifying images of arsenicosis-affected and healthy skin, demonstrating the potential of deep learning in medical image analysis.

Table 1. List of Software Components

Tool	**Functions**	**Other similar Tools (if any)**	**Why selected this tool**
Dataset	Collection of skin images for training and testing	None	Local relevance and authenticity to the target population
Pandas, Matplotlib, Seaborn	Understanding dataset characteristics and informing preprocessing steps	None	Provides essential insights and visualizations for data understanding
ResNet MobileNet	Model for classifying images into healthy and affected categories	GoogleNet Inception VGGNet	Strong performance in image classification tasks
Adam Optimizer	Optimization of the model's learning process	SGD, RMSprop	Efficient and adaptive learning rate
BCELoss	Measures the performance of the binary classification model	Mean Squared Error	Suitable for binary classification problems

3.3 Software Implementation

This project was implemented using a number of integrated software modules, beginning with data handling and pre-processing. The first stage was to collect and compile a dataset of skin photos from villages around Bangladesh's Chapainawabganj area. This dataset contained both healthy and arsenicosis-affected skin pictures. Exploratory Data Analysis (EDA) was then used to better understand the data distribution and features, which guided the preparation stages. Preprocessing entailed reducing photographs to a consistent size, standardizing pixel values, and expanding the dataset to improve its size and diversity, hence improving the model's capacity to generalize to new data.

The core lesson focused on creating and training a Convolutional Neural Network (CNN) for image classification. The CNN architecture was created to detect intricate patterns in skin scans, allowing it to distinguish between healthy and diseased skin. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and more than 20 epochs. The model's training performance was evaluated using binary cross-entropy loss. After training, the model was evaluated on a separate test set to determine its accuracy and robustness. Hyperparameter adjustment was done manually to improve the model's performance. The entire implementation was carried out utilizing common deep learning frameworks and packages, which ensured the project's efficiency and scalability.

Chapter 4

Investigation/Experiment, Result, Analysis and Discussion

The research required the creation and testing of two distinct Convolutional Neural Network (CNN) models for classifying photos of arsenicosis-affected and healthy skin. The models were trained using a sample from the main dataset that includes 1030 photos for training and 257 images for testing. The training was carried out over 20 epochs with a batch size of 32, a learning rate of 0.001, the Adam optimizer, and the Binary Cross-Entropy Loss (BCELoss) loss function.

Table 2. Hyperparameters for Training an Original Dataset

Hyperparameter	**Value**
Number of Epochs	20
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Loss Function	BCELoss
Train Size	1030 images
Test Size	257 images

ResNet-18:

During training and testing, the ResNet-18 model outperformed expectations. It has a train loss of 0.0204, showing low error in the training data. The model also achieved a train accuracy of 99.61%, demonstrating its ability to properly identify the great majority of training images. ResNet-18 obtained 98.44% accuracy on the test set, demonstrating its great ability to generalize to previously encountered data.

MobileNet v4:

The MobileNet v4 model, which was developed for efficiency and speed, also performed well, albeit with slightly lower metrics than ResNet-18. It had a train loss of 0.1000 and a train accuracy of 96.99 %. On the test set, MobileNet v4 achieved an accuracy of 95.72%, which is somewhat lower than ResNet-18 but still shows strong performance in classifying skin photos.

Overall, both models performed well in recognizing arsenicosis-affected skin, with ResNet-18 significantly outperforming MobileNet v4 throughout both the training and testing stages.

Table 3. Model Results (Original Dataset)

Model	Train loss	Train Accuracy	Test Accuracy
ResNet18	0.0204	0.9961	0.9844
MobileNet v4	0.1000	0.9699	0.9572

After checking the accuracies of the two models ResNet18 and MobileNet v4 on an original set of data, we have implemented eight more new models on the full dataset.

Table 4. Hyperparameters for Training the Dataset of Original and Augmented Images

Hyperparameter	Value
Number of Epochs	10
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Loss Function	BCELoss
Train Size	8143 images
Validation Size	1018 images
Test Size	1018 images

MobileNet V3 Large:

MobileNet V3 Large obtains the following three losses: training loss is the lowest with 0.0129 at the same time as validation loss of 0.0005, the lowest and the one with the highest goodness in one of the tests with 0.0007, additionally, the highest purity and perfectness with the accuracy of 99.53%, 100.00%, and 100.00%, respectively, which makes the whole process nowadays more interesting, thereby providing a solid foundation for future artificial intelligence (AI) improvements in terms of both robustness and computational efficiency.

EfficientNet:

EfficientNet has also introduced favorable results with training, validation, and test losses at low levels of (0.0060), (0.0027), and (0.0002), respectively, along with end-of-the-training correctness levels of 99.80%, 99.80%, and 100.00%, which shows effectively that the previously identified effective approach of model size regularization was adhered to through its task performance.

MobileNet V2:

Well, MobileNet V2 works with a very large model with a very small number of training losses (0.0131), validation losses (0.0095), even with near perfection of the test losses (0.0028), and high scores of 99.63%, 99.61%, and 100.00% in the validation and test parts of the test, with similarly high results in the corresponding training parts of 99.63% and 99.6%. It is clear from the first glance that the network skips into the second segmentation category.

RestNet 50:

For the first time, the ResNet50 loss is high on the training (0.0262) and the validation (0.0268) set, but the accuracies of 99.21% and 99.02% are still low. Along with the test loss of 0.0056 and accuracy of 99.90%, the system is capable of complex tasks even if it has slightly away-from-ideal validation losses.

MobileNet V3 Small:

MobileNet V3 Small, on the other hand, has lower validation and test scores than its "large" sibling and EfficientNet; the former goes as 98.53% and 99.51% for the validation and test, respectively, with a training error of 0.0097 and a test loss of 0.0160 as the only indicators of the level of training performance, thus posing as a sign that handling more complex datasets is simply beyond one's capability.

GoogleNet:

In the same way as MobileNet V3 Small, GoogleNet also presents low training and validation losses, even with the lower accuracies on the validation (99.51%) and the test (99.31%), which are less accurate than the other models. Interesting, but not the best if compared to other models.

VggNet16 and VggNet19:

VggNet16 as well as VggNet19 have the training (0.7529, 0.7974), validation (0.6930, 0.6937), and test losses (0.6930, 0.6937) being very high with a really poor performance of the model as they are equally above the accurate prediction across all phases (52.75%, 50.98%, 50.93% VggNet16 and 53.39%, 49.02%, 49.07% VggNet19), which could be a sign of overfitting or the inability of the system to perform the necessary function.

Table 5. Model Results (Original + Augmented Dataset)

Model	Train Loss	Train Accuracy	Val Loss	Val Accuracy	Test Loss	Test Accuracy
MobileNet V3 Large	0.0129	99.53%	0.0005	100%	0.0007	100.00%
EfficientNet	0.0060	99.80%	0.0027	99.80%	0.0002	100.00%
MobileNet V2	0.0131	99.63%	0.0095	99.61%	0.0028	100.00%
ResNet50	0.0262	99.21%	0.0268	99.02%	0.0056	99.90%
MobileNet V3 Small	0.0097	99.75%	0.0506	98.53%	0.0160	99.51%
GoogleNet	0.0097	99.68%	0.0172	99.51%	0.0161	99.31%

VggNet16	0.7529	52.75%	0.6930	50.98%	0.6930	50.93%
VggNet19	0.7974	53.39%	0.6937	49.02%	0.6937	49.07%

Evaluation Metrices:

MobileNet V3 Large:

```
Classification Report:
              precision    recall  f1-score   support

    Infected       1.00      1.00      1.00       519
Not Infected       1.00      1.00      1.00       500

    accuracy                           1.00      1019
   macro avg       1.00      1.00      1.00      1019
weighted avg       1.00      1.00      1.00      1019
```

Figure 4.1. Classification Report for MobileNet V3 Large

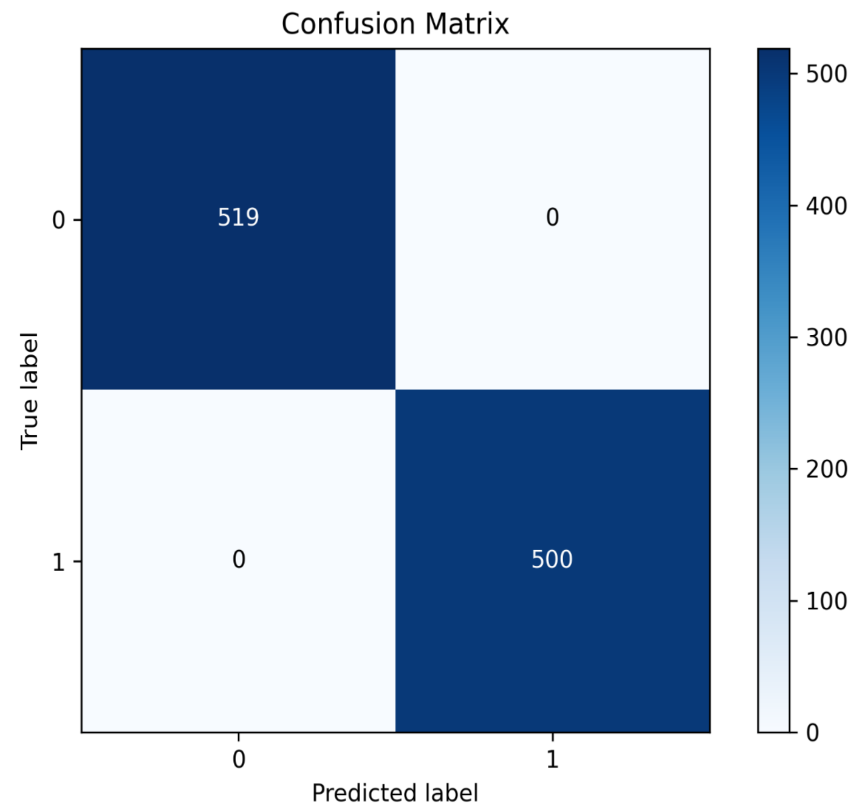

Figure 4.2. Confusion Matrix for MobileNet V3 Large

EfficientNet:

```
Classification Report:
              precision    recall  f1-score   support

    Infected       1.00      1.00      1.00       519
Not Infected       1.00      1.00      1.00       500

    accuracy                           1.00      1019
   macro avg       1.00      1.00      1.00      1019
weighted avg       1.00      1.00      1.00      1019
```

Figure 4.3. Classification Report for EfficientNet

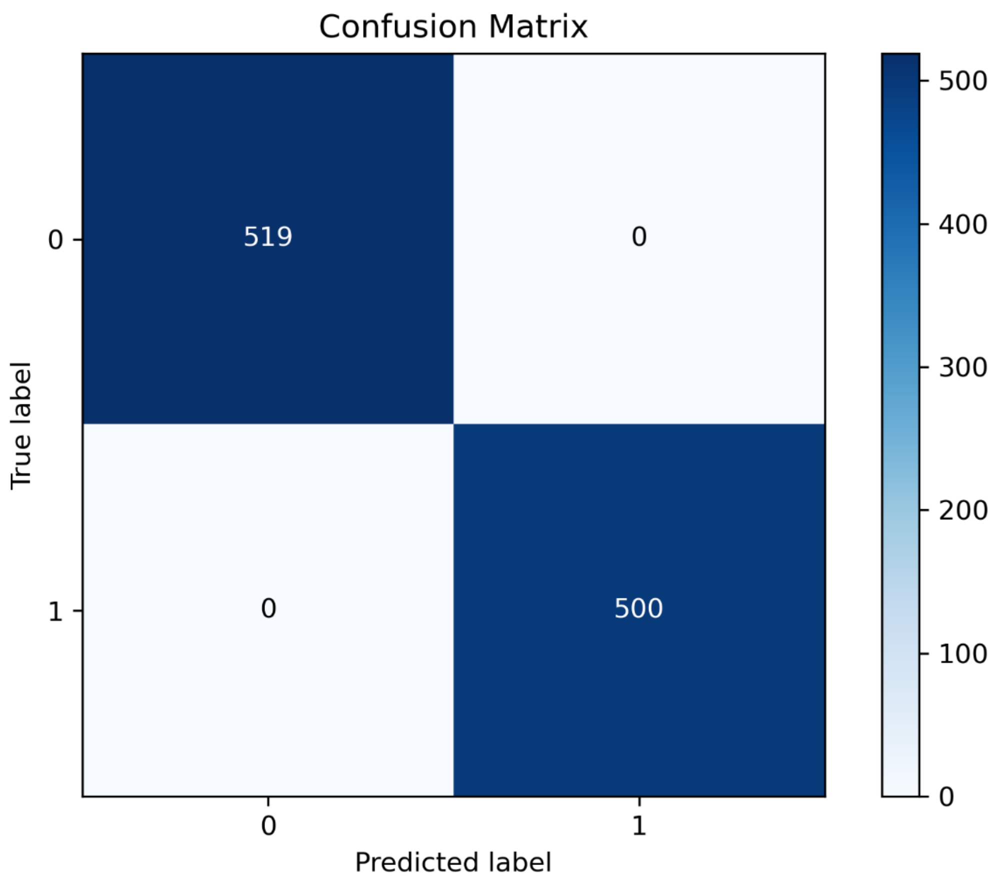

Figure 4.4. Confusion Matrix for EfficientNet

ResNet50:

Classification Report:

	precision	recall	f1-score	support
Infected	1.00	1.00	1.00	519
Not Infected	1.00	1.00	1.00	500
accuracy			1.00	1019
macro avg	1.00	1.00	1.00	1019
weighted avg	1.00	1.00	1.00	1019

Figure 4.5. Classification Report for ResNet50

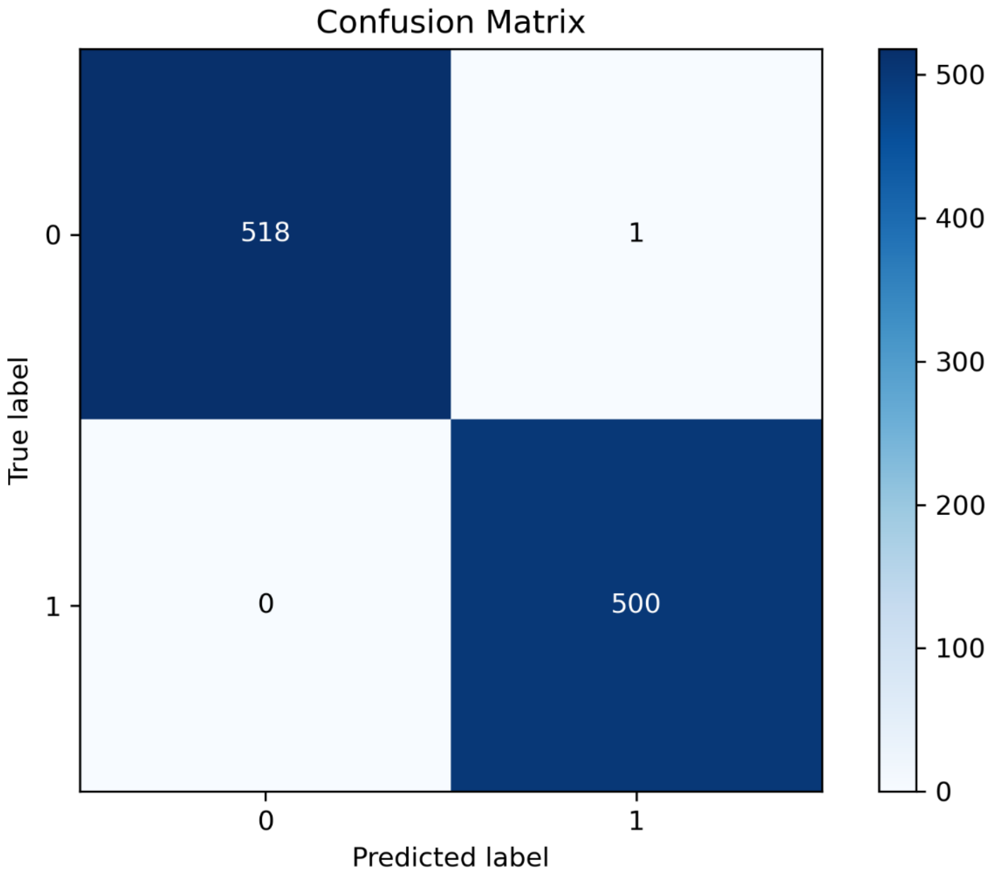

Figure 4.6. Confusion Matrix for ResNet50

Chapter 5 Impacts of the Project

5.1 Impact of this project on societal, health, safety, legal and cultural issues

Social Impact:

This project can help people in areas with arsenic poisoning, especially in places like Chapainawabganj. It uses pictures to quickly and accurately identify skin problems caused by arsenic. This early detection can help people get treatment sooner, preventing serious health issues like skin cancer and organ damage. Even in places with fewer doctors, healthcare workers can use this technology to identify potential cases and provide early care. By tracking people at risk, we can find areas with high arsenic levels and take steps to reduce exposure. This project can also raise awareness about the dangers of arsenic poisoning, encouraging people to protect themselves.

Ethical Responsibilities:

The ethical responsibility surrounding "Image Classification and Analysis of Arsenicosis affected Skin" is multifaceted, encompassing data privacy, algorithmic fairness, and accessibility:

Individuals whose images are used for training and testing the AI system must provide informed consent. This means they understand how their data is used (anonymously) and have the right to withdraw consent at any point. Image must be rigorously anonymized before being used to train or test the AI. This protects patient privacy and prevents potential misuse of personal data. The AI model needs to be trained on a vast dataset that reflects the diversity of skin tones and the varying presentations of arsenicosis. This helps to mitigate bias in diagnosis based on race, ethnicity, or disease severity. The AI's decision-making process should be transparent. Healthcare professionals should be able to understand how the AI arrives at its conclusions regarding the presence or absence of arsenicosis. In an area that struggles with arsenic contamination such as Chapainawabganj (which we refer to in this project), the technology should be affordable and readily available. This ensures that the technology bridges the healthcare gap instead of widening it by being inaccessible in the areas with the greatest need. The primary goal should be to improve public health outcomes in communities affected by arsenic contamination. This might involve making the tool open-source or offering it at a subsidized cost in these areas. We should consider ways to use the technology to promote public awareness and understanding of the condition. Involving affected communities throughout the development process helps build trust and ensures the technology addresses their needs effectively.

Professional Responsibilities:

Ensure that researchers involved in the project possess the necessary expertise and competence in image classification, analysis techniques, and arsenicosis-related research. Hence one must stay updated with relevant methods and advancements in this field. Follow established standards, guidelines, and best practices for conducting research involving image classification and analysis, as well as research involving human participants. Ensure transparency and reproducibility in all aspects of the project, including data collection, analysis methods, and results interpretation. Identify and manage any potential conflicts of interest that may arise during the course of the project. Disclose any financial, institutional, or personal relationships that could influence the research process or outcomes. Foster collaboration and teamwork among researchers, collaborators, and stakeholders involved our project. Ensure effective communication, coordination, and cooperation to achieve project objectives and milestones. Research findings should be disseminated through appropriate channels. Ensure that results are communicated accurately, clearly and responsible to relevant audiences. By adhering to these professional responsibilities, we can conduct the project "Image Classification and Analysis of Arsenicosis affected Skin" with professionalism, rigor, and commitment to advancing scientific knowledge and improving public health outcomes.

Cultural Impact:

Arsenic poisoning is a serious health problem in many rural and poor areas of Bangladesh. When people have this condition, they often get skin problems that can make others treat them differently. This can lead to feelings of shame and loneliness, as people may be excluded from social activities or judged unfairly.

This project aims to address these social issues by using technology to diagnose arsenic poisoning. By making diagnosis easier and more accessible, it helps to remove the stigma associated with the condition. People are more likely to seek help when they understand that it's a medical issue, not something to be ashamed of. This also helps to build trust in modern healthcare and empowers communities to take action against arsenic poisoning.In the end, this project helps to break down social barriers, reduce stigma, and promote equality. It leads to healthier and more accepting communities

5.2 Impact of this project on environment and sustainability

Social effects:

The project "Image classification and analysis of arsenicosis affected skin" has the potential for significant social impact in areas affected by arsenic contamination, particularly in regions like Chapainawabganj. Here's how-

1. **Healthcare Improvement:**

By using image classification and analysis techniques, the project can aid in early detection and diagnosis of arsenicosis, a condition caused by long-term exposure to arsenic-contaminated water. Early detection allows for prompt medical intervention, potentially preventing severe health complications associated with arsenicosis, such as skin lesions, skin cancer, and internal organ damage.

2. **Earlier diagnosis and treatment:**

Arsenic exposure can lead to serious health problems, including skin cancer. By enabling faster and more accurate diagnosis of arsenicosis through image analysis, this project could help people get treatment sooner and improve their health outcomes.

3. **Improved access to healthcare in remote areas:**

In areas with limited access to dermatologists, this technology could be used by healthcare workers with less training to identify potential cases of arsenicosis. This would allow for earlier intervention and potentially reduce the burden of arsenic-related diseases.

4. **Better monitoring of arsenic exposure:**

The ability to automatically analyze skin images for signs of arsenicosis could be used to monitor populations at risk of exposure. This information could be used to identify areas with high levels of arsenic contamination and take steps to reduce exposure.

5. **Increased awareness of arsenic poisoning:**

This project could raise awareness of the dangers of arsenic exposure and encourage people to take steps to protect themselves. This could be especially important in areas where arsenic contamination is a common problem.

Environmental effects:

While the primary focus of the project "Image classification and analysis of arsenicosis affected skin" is on the health and well-being of individuals affected by arsenic contamination, it indirectly contributes to environmental impact through several avenues:

1. **Identification of contaminated Areas:**

By analyzing images of arsenicosis affected skin, the project can help identify regions where arsenic contamination in water sources is prevalent. This information is crucial for environmental monitoring and remediation efforts to mitigate further contamination and restore affected ecosystems

2. **Water resources management:**

Arsenic contamination in water sources not only affects human health but also has detrimental effects on aquatic ecosystems. The project's findings can inform strategies for managing water resources more sustainably, such as implementing water treatment technologies or promoting alternative sources of safe drinking water, thus safeguarding environmental health

3. **Ecosystem protection:**

Addressing arsenic contamination can help protect the biodiversity and ecological integrity of affected areas. High levels of arsenic in water bodies can harm aquatic life, disrupt food chains, and degrade habitat quality. By addressing the root causes of contamination, the project indirectly contributes to preserving these ecosystems.

4. **Prevention of pollution:**

Through raising awareness and advocating for improved water quality standards, the project aids in preventing further pollution of water sources with arsenic and other contaminants. This proactive approach helps safeguard the environment from the adverse effects of pollution, including contamination of soil, air, and groundwater.

5. **Long-term sustainability:**

By promoting the adoption of sustainable practices and policies to address arsenic contamination, the project contributes to the long-term environmental sustainability of affected regions. This includes promoting renewable energy sources, reducing reliance on arsenic-containing pesticides, and advocating for land-use practices that minimize contamination risks.

Chapter 6

Project Planning and Budget

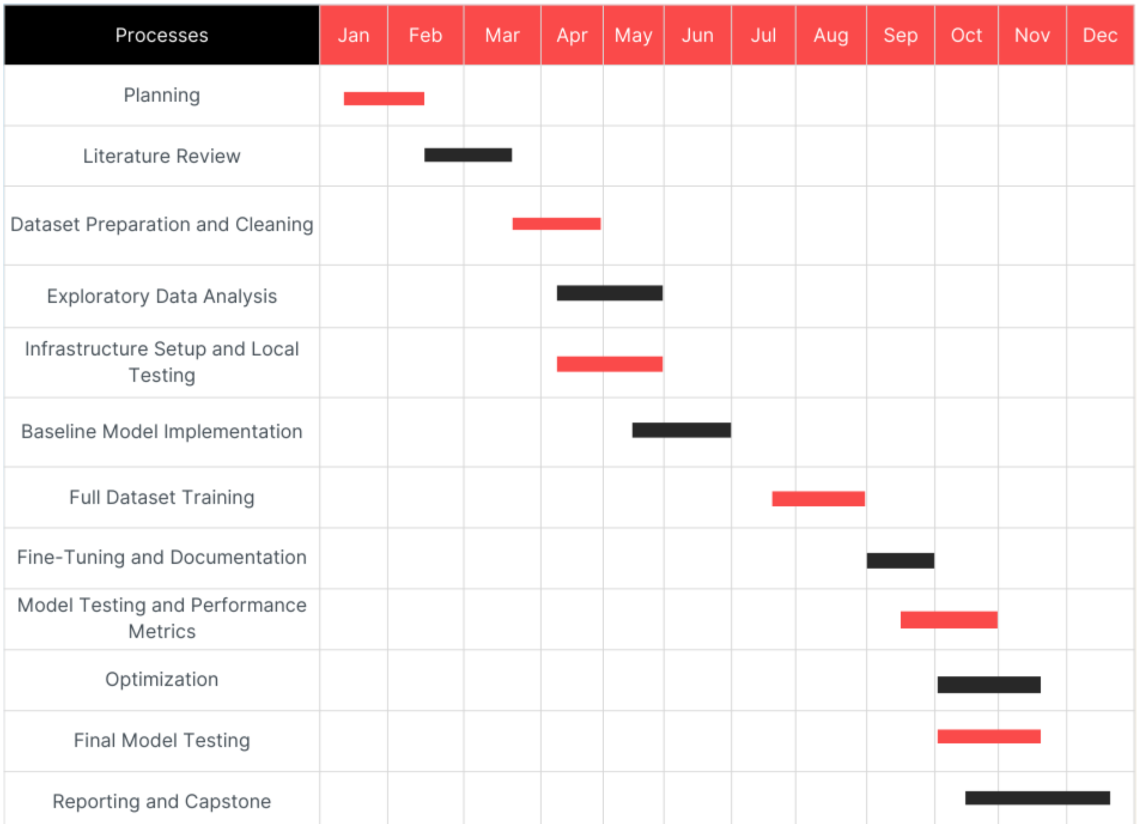

Figure 6.1: Gantt chart of Project Planning

Component	Unit Price (in BDT)	Quantity	Total cost (in BDT)
Nvidia Geforce RTX 4090	2,78,000	1	2,78,000
Intel Core i7 14700K Raptor Lake Processor	32,000	1	32,000
Corsair H150 Liquid CPU Cooler	6,000	1	6,000
Corsair HX750 750W ATX Power Supply	7,500	1	7,500
Corsair 16GB DDR5 7200MHz Desktop RAM	14,500	4	58,000
ASRock Z790 Pro RS ATX Motherboard	30,000	1	30,000
Subtotal = 4,11,500 BDT (3734 USD)			

Figure 6.2: Project Budget Table

Chapter 7 Complex Engineering Problems and Activities

7.1 Complex Engineering Problems (CEP)

Table 6. Complex Engineering Problem Attributes

Attributes		Addressing the complex engineering problems (P) in the project
P1	Feature Extraction	Identifying relevant features from the images that can distinguish between different stages of arsenicosis is essential. This may involve extracting texture, color, shape, and other visual features using techniques such as convolutional neural networks (CNNs) or handcrafted feature extraction methods.
P2	Image Preprocessing	Arsenicosis-affected skin images may vary in quality, lighting conditions, and background clutter. Preprocessing techniques such as noise reduction, normalization, and image enhancement may be required to improve the quality and consistency of the dataset.
P3	Class Imbalance	Imbalanced datasets, where some classes (severe arsenicosis cases) may be underrepresented, can bias the model's performance. Techniques such as data augmentation, oversampling, or using specialized loss functions can help mitigate this issue.
P4	Interpretability	Understanding how the model makes predictions is crucial, especially in medical applications where interpretability is essential for gaining trust from clinicians and patients. Techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) can help visualize which parts of the image are most important for classification.
P5	Integration with Clinical Workflow	The developed model should be seamlessly integrated into the clinical workflow to provide actionable insights to healthcare professionals. This may involve developing user-friendly interfaces, integrating with electronic health record systems, and providing decision support tools.

7.2 Complex Engineering Activities (CEA)

Table 7. Complex Engineering Problem Activities

Attributes		**Addressing the complex engineering activities (A) in the project**
A1	Data Process	Data Acquisition (Gathering Images & Ethical Considerations), Data Preprocessing (Standardization and Normalization, annotation, data splitting), Feature Extraction (Color Features, Texture Features, Shape Features)
A2	PyTorch	By leveraging PyTorch's robust features and flexibility, used pre-trained CNN models and tools for training/testing.
A3	Optimizer	Using an appropriate optimizer like Adam can help in efficiently training the convolutional neural networks by ensuring stable and fast convergence to an optimal set of weights, thereby improving the accuracy of the arsenicosis diagnosis from skin images.
A4	ResNet18	ResNet is an appealing option for the project because of their capacity to handle deep architectures and solve the vanishing gradient problem.Using ResNet's characteristics, this project aims to achieve high accuracy, rapid training, robust performance, and scalability, resulting in a more effective and reliable diagnostic tool for identifying arsenicosis from skin pictures.
A5	MobileNet v4	Incorporating MobileNet into the project improves efficiency, scalability, and deployment flexibility. MobileNet's ability to give fast and accurate predictions on resource-constrained devices makes it a good choice for real-world medical applications that require quick and trustworthy diagnostics.

Chapter 8 Conclusions

8.1 Summary

This project focuses on developing a deep learning-based system to classify arsenicosis-affected skin, addressing a significant public health challenge in rural Bangladesh. Utilizing a unique dataset of 8,892 augmented and 1,482 original images from Chapainawabganj villages, the study evaluates various state-of-the-art models, including EfficientNet, MobileNet, ResNet, and SimCLR. Notably, SimCLR and EfficientNet achieved 100% accuracy, demonstrating the efficacy of both supervised and self-supervised learning approaches. GradCAM integration provided explainability, offering visual insights into model predictions and fostering transparency.

The project underscores the potential of AI in healthcare, particularly for resource-constrained settings. By delivering accurate, scalable, and interpretable solutions, this work not only enhances early detection of arsenicosis but also paves the way for better disease management and intervention. While the models performed exceptionally, the study identifies areas for improvement, such as expanding annotated datasets, improving explainability techniques, and testing generalizability across diverse datasets to refine the system further.

8.2 Limitations

While our project using deep learning for image classification and analysis of arsenicosis in Bangladeshi people has immense potential, there are limitations to consider. Firstly, the accuracy of the deep learning model relies heavily on the quality and size of the training data. Collecting a large and diverse dataset of labeled skin images, encompassing various severities and skin tones, can be challenging. Additionally, obtaining accurate diagnoses from dermatologists for training data can be time-consuming and resource-intensive. Secondly, deep learning models can be complex and require significant computational power to train and run. This may limit accessibility in rural areas of Bangladesh where access to high-end computing facilities might be scarce. Finally, there are ethical considerations around data privacy and ensuring informed consent from participants, especially in sensitive medical projects. Addressing these limitations will be crucial for ensuring the robustness, generalizability, and responsible implementation of our project.

8.3 Future Improvement

One key area for future improvement is expanding the dataset to include a more diverse range of images, encompassing varying stages of arsenicosis, different lighting conditions, and data from multiple regions. This expansion will improve the model's generalizability and robustness when applied to real-world scenarios. Additionally, collecting more annotated data will help address the current limitations in dataset size and quality.

Advancements in Explainable AI (XAI) are another important direction. While GradCAM offered basic visual interpretability, incorporating techniques like SHAP or integrated gradients can provide more detailed insights into the decision-making process. These advancements will help build greater trust in AI-driven healthcare solutions.

Improving computational efficiency is also critical. Techniques such as model pruning, quantization, and knowledge distillation can reduce resource requirements, making the system more suitable for deployment in resource-constrained settings.

Finally, testing the model in real-world clinical environments and integrating it into mobile or web-based healthcare platforms can significantly enhance its accessibility. Such integration would allow healthcare providers in rural areas to leverage this tool for early detection and better management of arsenicosis, maximizing its impact on public health.

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