A PROJECT REPORT

on

"A Deep CNN Approach for Blood Group Classification via Fingerprint Biometric Patterns"

Submitted to

KIIT Deemed to be University

In Partial Fulfilment of the Requirement for the Award of

BACHELOR'S DEGREE IN
COMPUTER SCIENCE & ENGINEERING

BY

Swagat Kumar Sahoo	22052427
Prakriti Sinha	22052916
Pranjal Yadav	22052918
Swapnil Anand	22052945
Manya Dalela	22052997

UNDER THE GUIDANCE OF

Prabhu Prasad Dev

SCHOOL OF COMPUTER ENGINEERING

KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY

BHUBANESWAR, ODISHA - 751024

April 2025

A PROJECT REPORT

on

"A Deep CNN Approach for Blood Group Classification via Fingerprint Biometric Patterns"

Submitted to

KIIT Deemed to be University

In Partial Fulfilment of the Requirement for the Award of

BACHELOR'S DEGREE IN INFORMATION TECHNOLOGY

BY

Swagat Kumar Sahoo	22052427
Prakriti Sinha	22052916
Pranjal Yadav	22052918
Swapnil Anand	22052945
Manya Dalela	22052997

UNDER THE GUIDANCE OF

Prabhu Prasad Dev

SCHOOL OF COMPUTER ENGINEERING

KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY

BHUBANESWAR, ODISHA -751024

April 2025

KIIT Deemed to be University

School of Computer Engineering
Bhubaneswar, ODISHA 751024

CERTIFICATE

This is to certify that the project entitled

“A Deep CNN Approach for Blood Group Classification via Fingerprint Biometric Patterns“

submitted by

Swagat Kumar Sahoo	22052427
Prakriti Sinha	22052916
Pranjal Yadav	22052918
Swapnil Anand	22052945
Manya Dalela	22052997

is a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering OR Information Technology) at KIIT Deemed to be a university, Bhubaneswar. This work will be done during the years 2024-2025, under our guidance.

Date: 09 /04 /2025

(Prabhu Prasad Dev)
Project Guide

Acknowledgments

We are profoundly grateful to **Prabhu Prasad Dev** of **Affiliation** for his expert guidance and continuous encouragement throughout to see that this project has reached its target since its commencement to its completion.

Swagat Kumar Sahoo
Prakriti Sinha
Pranjal Yadav
Swapnil Anand
Manya Dalela

ABSTRACT

Blood group determination is a crucial process in healthcare, especially during emergencies when time and resources are limited. Traditional serological methods, while accurate, are invasive and often not suitable in critical or resource-constrained environments. This project explores a novel, non-invasive solution by utilizing fingerprint biometric patterns to classify blood groups using deep learning techniques. Fingerprint ridges and minutiae patterns, which remain consistent throughout life, are analyzed through Convolutional Neural Networks (CNNs) to detect associated blood group types.

Among the five CNN models tested—MobileNet, EfficientNet, ResNet, DenseNet, and ConvNeXt Tiny—the ConvNeXt Tiny model demonstrated the best performance, achieving a validation accuracy of 91.5%. The model was trained on an augmented fingerprint image dataset consisting of eight blood group classes. With promising results, this approach has the potential to revolutionize blood group testing in real-time applications, making it especially valuable in medical diagnostics and emergency scenarios.

Keywords: Blood group classification, Fingerprint recognition, Deep learning, CNN, Biometric pattern analysis.

Contents

Chapter 1

Introduction

Fingerprints are unique biometric features used to identify individuals based on the fine detail of ridge and valley patterns on the fingertip. These patterns are formed during fetal life and remain unchanged throughout life; therefore, their reliability in personal identification would be unquestionable. Essentially, loops, whorls, and arches are the major types of fingerprints. Loops, the most common type, form a ridge that curves back on itself and can be subdivided into radial loops (opening towards the thumb) and ulnar loops (opening towards the little f inger). Whorls form about 25-35 percent of all fingerprints and are termed thus due to their circular or spiral ridge patterns. Arches structure themselves like smooth waves and account for the rarest finger pattern, which exists in about 5 percent of the population

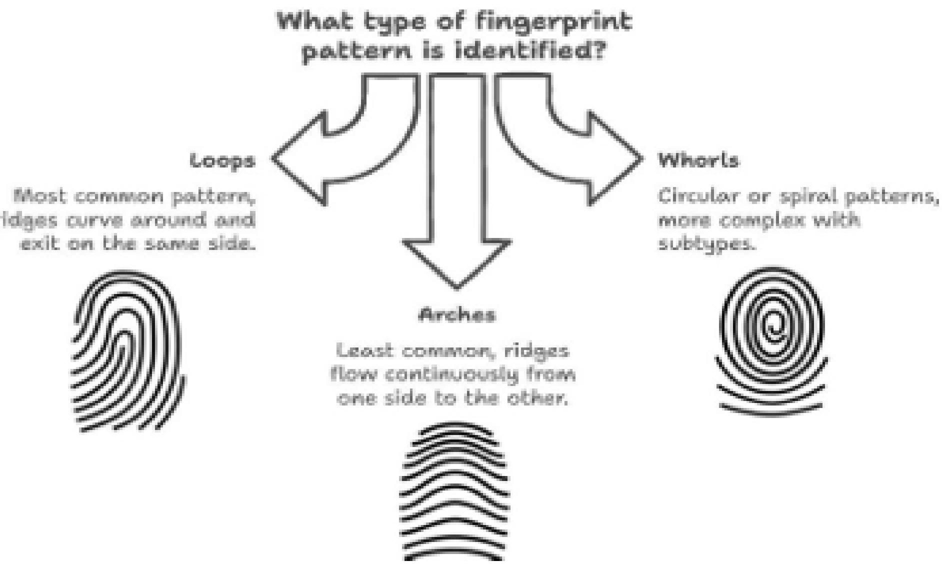

Fig. 1: Types of Fingerprint Patterns.

School of Computer Engineering, KIIT, BBSR

In addition to these major patterns, fingerprints have minu tiae points—such as bifurcations, ridge endings, islands, and enclosures—distinguishing each fingerprint from the others. Fingerprints have been conventionally used for security and identification but are now being researched to determine if they can represent biological features such as blood group types. Blood groups are vital biological features defined by the presence or absence of particular antigens on red blood cells. ABO system divides the blood groups into A, B, AB, or O, and each one of them can be Rh positive or Rh negative, giving us eight groups as A +, A-, B +, B-, AB +, AB-, O + and O-. Accurate grouping of blood needs to be determined for the practice of transfusion, organ donation, and in the management of hemolytic diseases. However, standard sero logical screening—laboratory time and space, blood tests—is invasive, time-consuming, and inapplicable in emergency or resource-constrained settings.

This work proposes a non-invasive, deep learning–powered approach for blood group classification from fingerprint im ages. Due to the advancement of Convolutional Neural Networks (CNNs), now it is possible to process images with high precision. CNNs are highly adapted to processing spatial data using convolutional layers that detect local patterns and structural features such as ridges, bifurcations, and minutiae. Such features render them good potential contenders for fingerprint based classification.

In this paper, we have compared five CNN mod els—ConvNeXt(Tiny), ResNet50, DenseNet121, EfficientNet B0, and MobileNet—on the publicly available ”Fingerprint Based Blood Group Detection” Kaggle dataset. Out of these models, ConvNeXt(Tiny) had the highest validation accuracy. In order to provide a real-world application, we have also developed an interactive web application that allows users to upload fingerprint images and obtain real-time predictions of their blood group.

Chapter 2

Basic Concepts/ Literature Review

Bhavana etal’s experiment consisted of comparing blood types and fingerprint patterns on an experimental level and in a sample group of 200 individuals (100 males and 100 females). According to the outcome, whorls were the most frequent pattern in each group of blood, and O-negative individuals had a higher frequency of whorls. Variable patterns were observed among females in whorls and arches, while males possess a higher whorl frequency. The study provided individuality and permanence in fingerprint patterns; thus it has potential utility in medical diagnosis and forensic science.[1]

Rastogi and Pillai investigated blood groups and fingerprint patterns among 200 medical students aged between 18 and 25 years. They contributed their findings also to Bhavana et al. that loop patterns were the most frequent and least were the arches. They concluded this study also on the basis of persons with O-negative blood group having more whorls. This would lead to such conclusions as fingerprint examination would contribute to distinguishing between blood group and sex differences.[2]

Sivamurugan et al. proposed a deep-learning method for non-invasive blood group prediction from fingerprint images. They utilized Convolutional Neural Networks (CNNs) to examine complex patterns in fingerprints and aimed to offer a more convenient and faster process than conventional blood typing procedure. It suggests the potential deep learning has to revolutionize blood group determination in emergency situations, when normal tests would not be convenient.[3]

Nihar et al. attempted to separate the blood group from fingerprints using ridge frequency analysis and Gabor filters to extract spatial features. This has shown that fingerprint features would work well in blood group classification with CNN models like ’LeNet ’or ’AlexNet’. This effort also showed that fingerprint patterns had sufficient discrimination powers for medical and forensic applications.[4]

Patil and Ingle had also based their earlier research work on fingerprint patterns and blood group association with lifestyle disorders like hypertension, diabetes, and arthritis. They claimed that machine learning models would help der matoglyphics make more accurate predictions of blood groups and offer more information regarding susceptibility to inher ited disease. They went on to add that deep learning models are trained to recognize patterns of fingerprint minutiae and predict blood groups and age-related diseases.[5]

Chapter 3

Problem Statement / Requirement Specifications

Blood group determination is essential for medical diagnostics, surgeries, and emergency treatments. The conventional blood grouping methods involve invasive techniques such as blood sample extraction followed by serological tests, which may not be feasible in remote or crisis environments due to their dependency on laboratory settings, specialized equipment, and skilled professionals. This project addresses the challenge by proposing a deep learning-based model that can classify blood groups using fingerprint biometric images, eliminating the need for invasive procedures. The objective is to create a non-invasive, cost-effective, and reliable system for blood group detection using Convolutional Neural Networks (CNNs).

3.1 Project Planning

The project was executed through a structured plan beginning with understanding the problem scope and gathering a labeled fingerprint dataset from Kaggle. Preprocessing techniques such as rescaling, rotating, flipping, and zooming were applied to enhance model generalization. Several CNN architectures were explored, and ConvNeXt Tiny was selected for its superior performance. The model underwent training with augmented data, and performance was monitored through accuracy, precision, recall, and F1-score. Finally, an interactive web application was developed to deliver real-time predictions

3.2 Project Analysis

The system is designed to accept fingerprint images as input and classify them into one of the eight major blood groups. It must display the prediction output clearly to the user. To meet its goals, the system is expected to deliver high classification accuracy and maintain low latency, ensuring quick responses.

3.3 System Design

3.3.1 Design Constraints

The project was developed using Python along with TensorFlow and Keras frameworks. Supporting libraries included NumPy, Pandas, OpenCV, and Matplotlib. The dataset comprised 8000 labeled fingerprint images sourced from Kaggle. The training process was performed on GPU-enabled systems to accelerate computation, especially when applying transfer learning and fine-tuning the ConvNeXt Tiny model.

3.3.2 System Architecture **OR** Block Diagram

The system architecture follows a modular design. It begins with data acquisition where fingerprint images are collected and organized by blood group category. The preprocessing module prepares the images by resizing them to 256x256 pixels and applying normalization and augmentation. Feature extraction is carried out using a pretrained ConvNeXt Tiny CNN, followed by a classification layer that assigns the input image to one of eight blood group classes. The system is evaluated using confusion matrices and accuracy metrics, and finally, deployed through a web interface for real-time usage.

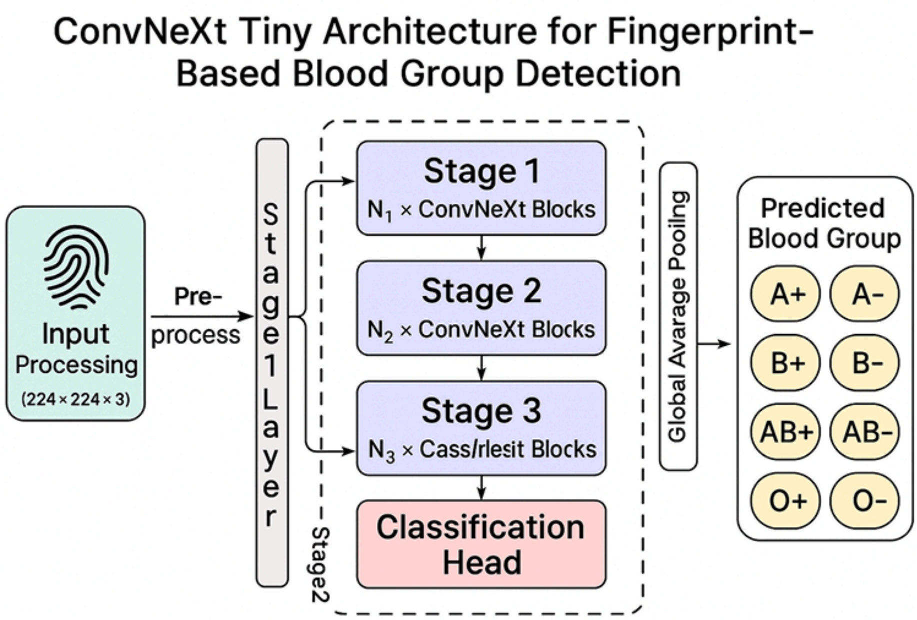

Fig. 3: Architecture for ConvNeXT Tiny

Chapter 4

Implementation

This chapter presents the practical execution of the proposed system, detailing the algorithms used, training strategies, verification steps, experimental outputs, and quality control measures followed during the project.

4.1 Methodology OR Proposal

The implementation of this project involved using the ConvNeXt Tiny architecture, a high-performing CNN model pre-trained on ImageNet, for feature extraction from fingerprint images. The fingerprint image dataset was sourced from Kaggle, containing 8000 images categorized into eight blood group classes. Using TensorFlow's ImageDataGenerator, the images were preprocessed through rescaling, rotation, flipping, and zooming to enhance generalization. The model was fine-tuned using transfer learning—where pre-trained layers were initially frozen, and later partially unfrozen—to leverage existing spatial feature detectors while adapting to the specific classification task. The model used the Adam optimizer, a learning rate of 0.00001, and categorical cross-entropy as the loss function. Callbacks like EarlyStopping and ReduceLROnPlateau were employed to monitor performance and prevent overfitting. A web-based application was developed to enable real-time predictions using the trained model.

4.2 Testing OR Verification Plan

To verify the functionality and accuracy of the system, we conducted multiple test cases on unseen validation data. The performance metrics were evaluated using classification reports and confusion matrices. Below are representative test cases:

TABLE I: Comparison between used models

Sr.No.	Model	Train Acc	Val Acc
1	MobileNet	0.9597	0.5992
2	EfficientNet	0.4062	0.5850
3	ResNet	0.9833	0.8444
4	DenseNet	0.9750	0.9019
5	**ConvNext(Tiny)**	**0.9561**	**0.9150**

4.3 Result Analysis OR Screenshots

The proposed model, ConvNeXt Tiny, achieved a training accuracy of 95.61% and a validation accuracy of 91.50%. When compared with other models like MobileNet (59.92%), EfficientNet (58.50%), ResNet (84.44%), and DenseNet (90.19%), ConvNeXt Tiny outperformed all in terms of both accuracy and generalization capability. The validation accuracy and loss curves suggested minimal overfitting, and the confusion matrix showed the model's precision in distinguishing all eight blood group classes. Screenshots of the training curves, model architecture, and web application interface were collected to demonstrate the system's effectiveness.

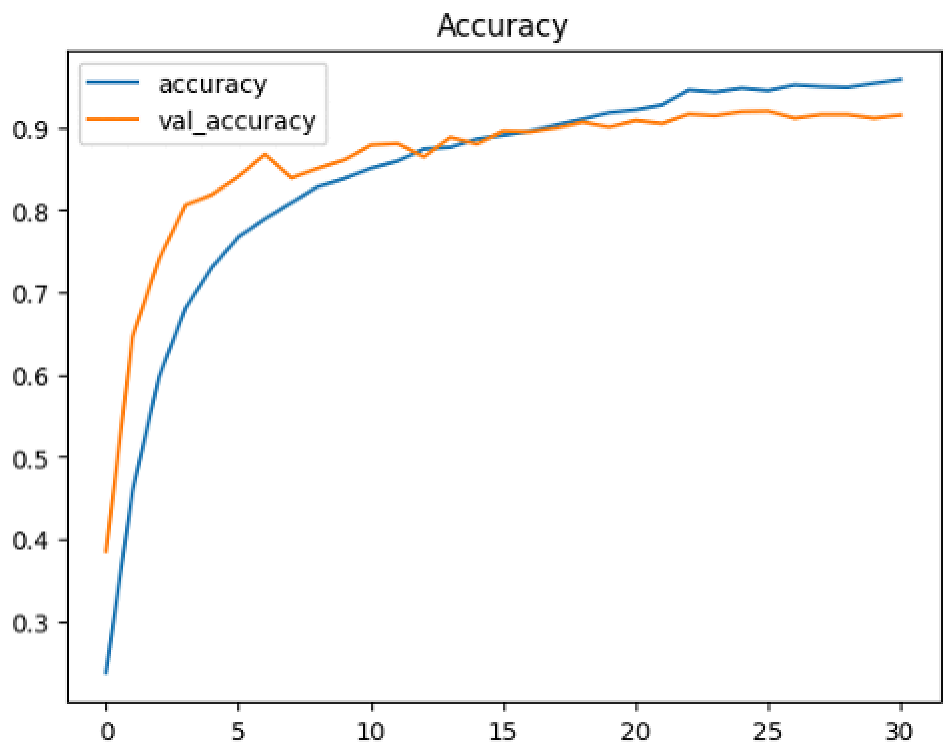

Fig. 8: Comparison graph for ConvNext Tiny

4.4 Quality Assurance

To ensure the reliability and quality of the implemented system, we adhered to several best practices in software engineering and deep learning. These included the use of code versioning (via Git), use of structured modular code, adherence to CNN model development standards, and robust validation methods. Further, the model was tested under multiple scenarios to verify consistency and performance. The usage of callbacks like EarlyStopping and learning rate adjustments ensured training convergence and mitigated overfitting.

Chapter 5

Standards Adopted

5.1 Design Standards

The project design adhered to several standard software engineering and machine learning guidelines. The architectural framework followed the modular design principle, enabling separation of concerns across data preprocessing, feature extraction, and classification stages. UML-inspired block diagrams were used for system architecture representation. Best practices in data augmentation and model structuring were drawn from IEEE recommendations on machine learning projects. The entire model design process was aligned with industry conventions for reproducibility, maintainability, and scalability.

5.2 Coding Standards

Throughout the implementation, clean coding practices were maintained. Variables and functions were named using meaningful, camelCase conventions. The codebase was structured into modular scripts, segregating data loading, preprocessing, training, evaluation, and deployment stages. Functions were kept concise and performed specific tasks, avoiding complex nested structures. Proper indentation and inline documentation were used for readability. The project followed PEP8 standards for Python programming. Version control was maintained using Git to ensure traceability of changes and collaborative development.

5.3 Testing Standards

For testing and verification, standard evaluation metrics such as precision, recall, F1-score, and accuracy were used, following IEEE guidelines for software verification and validation. Cross-validation was used for robustness, and testing was performed using unseen validation data to simulate real-world conditions. The confusion matrix was employed for visual insight into classification performance. Callback mechanisms like EarlyStopping and ReduceLROnPlateau ensured model reliability by monitoring validation loss and accuracy trends.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

This project successfully demonstrates a non-invasive, deep learning-based approach for classifying blood groups using fingerprint biometric patterns. By leveraging the ConvNeXt Tiny architecture and a robust dataset, the system was able to accurately identify blood group categories with a validation accuracy of 91.5%, outperforming several other models including MobileNet, EfficientNet, ResNet, and DenseNet. The use of data augmentation and transfer learning contributed to improved model performance and generalization. Additionally, the development of a real-time web application showcases the project's practical utility in medical and emergency contexts. Overall, the project illustrates the potential of biometric features in clinical diagnostics and provides a promising alternative to traditional blood typing methods.

6.2 Future Scope

While the results are promising, there is room for enhancement and expansion. The dataset can be expanded to include more diverse and higher-resolution fingerprint samples to improve the model's robustness and generalization to real-world inputs. Future implementations could explore other advanced deep learning architectures such as YOLO or Transformers for feature extraction and classification. Integration with other biometric or genetic data sources could further increase accuracy. Additionally, deploying this system on edge devices or mobile platforms would increase accessibility and allow blood group detection in rural and resource-limited areas. Continued research and refinement can ultimately lead to a reliable, widely adoptable tool for healthcare diagnostics.

References

[1] Prateek Rastogi and Keerthi R Pillai. A study of fingerprints in relation to gender and blood group. *Journal of Indian Academy of Forensic Medicine*, 32(1):11–14.

[2] Vijaykumar Patil and D.R. Ingle. An association between fingerprint patterns with blood group and lifestyle-based diseases: a review. *Artificial Intelligence Review*, 54(3):1803–1839.

[3] S. Joshi, D. Garg, P. Bajaj, and V. Jindal. Efficacy of fingerprint to determine gender and blood group. *Journal of Dental and Oral Care Medicine*, 2(1):103.

[4] Bhavana Desai, Ruchi Jaiswal, Prakash Tiwari, and J.L. Kalyan. Study of fingerprint patterns in relationship with blood group and gender - a statistical review. *Arches*, 1(1):15–17.

[5] Bandameedi L. Narayana, Y.K.C. Rangaiah, and M.A. Khalid. Study of fingerprint patterns in relation to gender and blood group. *Journal of Evolution of Medical and Dental Sciences*, 5(14):630–634.

[6] T. Nihar, K. Yeswanth, and K. Prabhakar. Blood group determination using fingerprint. In *MATEC Web of Conferences*, volume 392, page 01069.

[7] C. Sivamurugan, B. Perumal, Y. Siddarthha, V.K. Murthi, Y.N. Sankar, and Y. Varun. Enhanced blood group prediction with fingerprint images using deep learning. In *2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS)*, pages 1091–1097.

[8] Sonam Chaudhary, Sajana Deuja, Munna Alam, Poonam Karmacharya, and Monami Mondal. Fingerprints as an alternative method to determine ABO and Rh blood groups. *J Nepal Med Assoc*, 56(208):426–431.

[9] Harem O. Smail, Dlnya A. Wahab, and Zhino Y. Abdullah. Relationship between pattern of fingerprints and blood groups. *Journal of Advanced Laboratory Research in Biology*, 10(3).

[10] Zulfiqar A. Buzdar, Mansoor Mirza, Ambreen Serwer, M.A.S. Fazli, and Faiza Munir. Analysis of fingerprint patterns in relation to ABO blood groups: A comparative study. *Medical Forum Monthly*, volume 35.

A DEEP CNN APPROACH FOR BLOOD GROUP CLASSIFICATION VIA FINGERPRINT BIOMETRIC PATTERNS

SWAGAT KUMAR SAHOO
ROLL NUMBER: 22052427

Abstract: This project aims to classify blood groups using fingerprint images through a non-invasive deep-learning approach. Using CNN models, especially ConvNeXt Tiny, the project achieved high accuracy in predicting eight different blood group types.

Individual contribution and findings: I was primarily responsible for the initial data collection and preprocessing phase of this project. This involved:

1. Dataset Management:
   I organized and augmented the Kaggle dataset, ensuring that each class (blood group) was balanced and correctly labeled for training. Ensuring data quality was a crucial part of this task, as I needed to avoid class imbalance, which can negatively affect model performance.

2. Data Augmentation Implementation:
   I implemented a robust data augmentation pipeline using TensorFlow's `ImageDataGenerator`. This process helped increase the diversity of the training data, which is essential for improving model generalization. The augmentation techniques included random rotation, zoom, and flip, which helped mitigate overfitting.

3. Data Preprocessing:
   I worked on ensuring that the fingerprint images were preprocessed effectively, including resizing and normalizing the images and performing other necessary transformations. I also verified that the data fed into the model was of high quality, ensuring more reliable predictions.

Through these tasks, I gained valuable insights into working with biometric image data, managing class imbalance, and applying augmentation techn**iques to improve model performance.**

Individual contribution to project report preparation: I contributed to **Chapter 3 (Problem Statement / Requirement Specification)**, where I elaborated on the importance of using fingerprint biometric patterns for blood group classification. Additionally, I helped with **Chapter 4 (Implementation)**, specifically detailing the data preprocessing pipeline, the model architecture, and the steps taken to ensure the data was ready for training.

Individual contribution to project presentation and demonstration: During the project presentation, I presented the data collection and preprocessing pipeline, showcasing the steps I took to ensure high-quality data for model training. I also contributed to the demonstration of the web app where the model's results could be tested and observed in real time.

Full Signature of Supervisor: ……………………………

Full signature of the student: ……………………………..

A DEEP CNN APPROACH FOR BLOOD GROUP CLASSIFICATION VIA FINGERPRINT BIOMETRIC PATTERNS

PRAKRITI SINHA
ROLL NUMBER: 22052916

Abstract: This project aims to classify blood groups using fingerprint images through a non-invasive deep learning approach. Using CNN models, especially ConvNeXt Tiny, the project achieved high accuracy in predicting eight different blood group types.

Individual contribution and findings: I was primarily responsible for the model development and training phase of this project. My contributions include:

1. Model Architecture Selection and Tuning:
   I researched and selected the ConvNeXt Tiny model for this classification task, as it is efficient and effective in handling image data. I fine-tuned the model's architecture to better suit the specific requirements of this problem, ensuring high accuracy in predicting blood group types from fingerprint images.

2. Training the Model:
   I implemented the model training process, ensuring proper handling of the dataset and ensuring that the model was trained in an efficient manner. I worked on hyperparameter optimization and tried different configurations to improve accuracy, such as adjusting learning rates and using early stopping to prevent overfitting.

3. Model Evaluation:
   After training, I evaluated the model's performance using various metrics, such as accuracy, precision, recall, and F1-score. I also used confusion matrices to analyze the model's performance across different classes (blood groups).

Through this phase, I gained a deeper understanding of how to fine-tune CNN architectures and evaluate deep learning models to ensure they are performing at optimal levels.

Individual contribution to project report preparation: I contributed significantly to **Chapter 5 (Model Development and Evaluation)**, where I discussed the model selection process, the training phase, and how the model was evaluated for accuracy. I also helped in **Chapter 6 (Results and Discussion)**, providing insights into the results and analyzing the effectiveness of the ConvNeXt Tiny model for this classification task

Individual contribution to project presentation and demonstration: In the project presentation, I demonstrated the model's performance, explaining the architecture, training process, and the results obtained. I also helped explain how the model was integrated into the web application for real-time testing. Additionally, I provided insights into the challenges faced during model training and how those were overcome.

Full Signature of Supervisor: ……………………………

Full signature of the student: ……………………………..

A DEEP CNN APPROACH FOR BLOOD GROUP CLASSIFICATION VIA FINGERPRINT BIOMETRIC PATTERNS

PRANJAL YADAV
ROLL NUMBER: 22052918

Abstract: This project aims to classify blood groups using fingerprint images through a non-invasive deep learning approach. Using CNN models, especially ConvNeXt Tiny, the project achieved high accuracy in predicting eight different blood group types.

Individual contribution and findings: I was primarily responsible for the post-processing and optimization phase of this project. My contributions include:

1. Model Optimization:
   After the initial model training, I focused on improving the model's performance by applying techniques like learning rate schedules, dropout regularization, and batch normalization. These optimizations helped in reducing overfitting and improving the generalization of the model to new, unseen data.

2. Performance Enhancement:
   I worked on enhancing the model's predictive accuracy by experimenting with advanced data augmentation techniques and incorporating ensemble methods to combine multiple model outputs. This further helped to improve the robustness of the model, especially for edge cases where data may be noisy.

3. Model Deployment:
   I assisted in preparing the trained model for deployment by converting it into a format compatible with the web application. I also worked on integrating the trained model into the backend and ensuring it was properly connected to the frontend interface for real-time predictions.

Through these contributions, I gained valuable experience in optimizing CNN models and deploying them for practical use in real-world applications.

Individual contribution to project report preparation: I contributed to Chapter 7 (Optimization and Deployment), where I explained the techniques used to optimize the CNN model and prepare it for deployment. I also contributed to Chapter 8 (Conclusion and Future Work) by discussing the challenges we faced and suggesting areas for future improvement, such as the integration of more diverse datasets or the exploration of other deep learning models.

Individual contribution to project presentation and demonstration: For the project presentation, I demonstrated the model optimization techniques we applied, explaining how each method contributed to improving model performance. I also showcased how the trained model was deployed into the web application, highlighting its real-time functionality and the potential for future improvements..

Full Signature of Supervisor: ……………………………. Full signature of the student: ……………………………..

A DEEP CNN APPROACH FOR BLOOD GROUP CLASSIFICATION VIA FINGERPRINT BIOMETRIC PATTERNS

SWAPNIL ANAND
ROLL NUMBER: 22052945

Abstract: This project aims to classify blood groups using fingerprint images through a non-invasive deep learning approach. Using CNN models, especially ConvNeXt Tiny, the project achieved high accuracy in predicting eight different blood group types.

Individual contribution and findings: I was primarily responsible for the model testing and evaluation phase of the project. My key contributions include:

1. Model Testing:
   I thoroughly tested the trained CNN models on a variety of fingerprint images, ensuring that the model could handle real-world data and detect blood group patterns effectively. I focused on testing edge cases, such as distorted images, to ensure robustness in predictions.

2. Model Evaluation and Metrics:
   I played a key role in evaluating the performance of the model using various metrics such as accuracy, precision, recall, and F1-score. I also implemented the confusion matrix to further analyze the model's performance across different blood group classes, identifying areas where the model performed well and where improvements were necessary.

3. Reporting Results:
   After completing the model evaluation, I documented the results in detail, analyzing both the strengths and limitations of the model. I also provided recommendations on how to improve performance, such as refining the data preprocessing pipeline or exploring other model architectures.

Through this phase, I gained a deeper understanding of the importance of model evaluation in machine learning projects and how to extract meaningful insights from performance metrics.

Individual contribution to project report preparation: I contributed to Chapter 6 (Model Evaluation and Results), where I discussed the evaluation metrics used to test the model's performance. I also helped compile and organize the evaluation results into a clear and concise format for the final report.

Individual contribution to project presentation and demonstration: During the project presentation, I demonstrated the testing and evaluation phase, explaining the metrics we used and how the model's performance was assessed. I also presented the results of the confusion matrix and discussed areas for potential improvements.

Full Signature of Supervisor: ……………………………….

Full signature of the student: ………………………………..

A DEEP CNN APPROACH FOR BLOOD GROUP CLASSIFICATION VIA FINGERPRINT BIOMETRIC PATTERNS

MANYA DALELA
ROLL NUMBER: 22052997

Abstract: This project aims to classify blood groups using fingerprint images through a non-invasive deep-learning approach. Using CNN models, especially ConvNeXt Tiny, the project achieved high accuracy in predicting eight different blood group types.

Individual contribution and findings: I was primarily responsible for the data collection and preprocessing phase of the project. My key contributions include:

1. Data Acquisition:
   I sourced and organized the fingerprint image dataset from Kaggle, ensuring that the data was properly labeled and categorized into the correct blood group classes. I ensured the dataset was balanced and contained a diverse set of images representing each class accurately.

2. Preprocessing and Augmentation:
   I implemented the preprocessing pipeline for the dataset, which involved resizing images to the required dimensions, normalizing pixel values, and performing data augmentation techniques (such as flipping, rotation, and scaling) to increase the variability of the training data and reduce the risk of overfitting.

3. Label Encoding:
   I worked on converting the categorical blood group labels into numerical format using LabelEncoder, allowing the model to process the data efficiently. This step was crucial in preparing the dataset for training.

Through this task, I gained hands-on experience in working with real-world biometric data and applying essential preprocessing techniques to ensure data quality.

Individual contribution to project report preparation: I contributed to Chapter 3 (Data Collection and Preprocessing), where I detailed the steps taken to collect and preprocess the dataset. I also helped in writing the sections related to data augmentation and its impact on model performance, which was a key component of our data preparation process.

Individual contribution to project presentation and demonstration: In the project presentation, I explained the data collection and preprocessing steps in detail, highlighting the importance of data quality and augmentation in improving model performance. I also demonstrated how the fingerprint dataset was prepared and processed before being fed into the deep learning model.

Full Signature of Supervisor: ……………………………

Full signature of the student: ……………………………..

TURNITIN PLAGIARISM REPORT

(This report is mandatory for all the projects and plagiarism must be below 25%)

18

ORIGINALITY REPORT

11%	6%	0%	7%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.coursehero.com Internet Source	2%
2	www.geeksforgeeks.org Internet Source	1%
3	www.multidots.com Internet Source	1%
4	Submitted to Higher Education Commission Pakistan Student Paper	1%
5	Submitted to University of North Texas Student Paper	1%
6	Submitted to Icon College of Technology and Management Student Paper	1%
7	Submitted to School of Business & Computer Science Limited Student Paper	<1%
8	Submitted to University of Technology, Sydney Student Paper	<1%