Comparing the Quality of Fingerprint Images by Two Different Sensors

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Abstract *– In the world of biometric authentication, the quality of fingerprint images is most important for ensuring the accuracy of recognition systems. This study takes part in a comparative analysis of image quality from optical and light-emitting (LES) sensors, using the MASIVE and SOCOFing datasets and the NFIQ2 tool for impartial quality assessment to study the correlation between image quality and sensor type. After tough data collection because of limited data available for fingerprints and pre-processing, the project further assesses the influence of metadata such as gender and finger type on image quality. Initial findings indicate that light-emitting sensors are better able to capture high-resolution images leading to higher NFIQ scores. This analysis also digs into the impact of metadata, showing that thumb fingerprints consistently yield better-quality images. Also, high minutiae count does not guarantee higher image quality. This study provides important insights into sensor performance and settles the preliminary work for future developments in biometric technology.*

1 Introduction

In the world of biometric authentication, fingerprint recognition is considered a backbone, playing an important role in identification and authentication systems across the world. The effectiveness of these systems is mainly dependent upon the accuracy and reliability of fingerprint image acquisition, a process promoted by the availability of an array of sensor technologies. Fingerprint scanners use various technologies - such as optical, light-emitting, capacitive, solid-state and many more - to capture individual fingerprint images. Given the crucial nature of fingerprint-based authentication, the quality of the captured fingerprint images is important. High-quality images increase the likelihood of accurate matches in recognition algorithms, which leads to higher security and efficiency of biometric authentication systems.

The importance of image quality in fingerprint recognition systems cannot be overemphasised, as it directly affects the success rate of fingerprint-matching algorithms [1]. A poor fingerprint image can lead to mismatches in the fingerprint recognition system, with possibly acute suggestions in different operational settings. Understanding this, there is an ongoing struggle within the research community to enhance the quality assessment tools for fingerprint images. Such tools help evaluate and ensure the quality of images captured by different sensors, eventually lowering the risk of mismatches.

This project aims to contribute to this field of research by conducting a comparative analysis of fingerprint images obtained from two different sensors: optical sensors and light-emitting sensors. Using two existing fingerprint datasets such as MASIVE [2] collected using a light-emitting sensor and SOCOFing [3] collected using an Optical sensor, this analysis will focus on assessing the quality of images based on relevant metadata shared by both datasets. The quality assessment of fingerprint images will be performed using the NFIQ- NIST(National Institute of Standards and Technology) Fingerprint Image Quality tool [1], a standardized software for evaluating the quality of Fingerprint images.

The NFIQ tool examines the complexity of fingerprint images, inspecting elements such as sharpness and contrast, and minutiae details, which are critical for accurate identification. By assigning a numerical score that ranges from 1 for lowest quality to 100 for highest quality, the NFIQ2 tool enables us to build a standardized baseline for quality comparison.

There is a lot of research out there comparing optical sensors to different sensors. This project aims to provide insights into fingerprint image quality assessment by fingerprint images captured by Optical sensors and Light-emitting sensors and evaluating them with the NFIQ2 tool. Additionally, it seeks to identify the influence of metadata such as gender, hand and finger type of fingerprint images, address challenges with image resolution and propose practical solutions to enhance fingerprint image quality.

This project report has multiple sections. The background section contains details about the problem and previous research done on the same or related topics. I have three added subsections in the literature review to relate to the aims of the project. The specification section contains details about the dataset and tools used for this project and the reason behind selecting them as well as required permissions and project plan. The design section of the report contains details about the approach I took to work on this project which is a data-driven approach and waterfall model. As this is a more research-oriented project, the implementation section contains details about image manipulation to make images ready for processing through NFIQ2 which is a standard fingerprint evaluation software, and the evaluation section of the report contains data analysis information on the output given by NFIQ2. Later, the appraisal section has comments about how well the project was executed and what could have been done better. The summary and conclusion section has details about the outcome gathered during the data analysis phase. The future section has details about limitations and future work that can be done on this project.

2 Background

Biometrics means biological measurements or physical characteristics of an individual that can be used for identification [20]. Over the years, the world has adopted biometrics as a security method as well as it cannot be stolen or forgotten and can provide a higher level of security to others [19]. Fingerprint technology has become an important factor in our security-conscious world, providing access to everything from smartphones to high-security services. These systems work by capturing and analysing the individual ridges and valleys of human fingerprints. However, the accuracy and reliability of fingerprint recognition depend on an important factor, which is the quality of the captured fingerprint image.

Figure 1: Sample fingerprint images from the SOCOFing dataset

The quality of fingerprint images depends on several factors, some related to the sensor capturing the image and others related to the user's finger.

There are a variety of sensor technologies available such as optical, capacitive, or light-emitting sensors and more. All of these come with different capabilities to capture clear and detailed fingerprints. Higher Sensor resolution sensors typically try to capture more detailed ridges and valleys of fingerprints resulting in higher quality images. Along with this placement of the finger to the sensor and applied pressure can lead to inaccurate and incomplete fingerprint images.

User factors like dry, cracked, or oily skin can affect fingerprint image clarity as well. Scars and wounds in the fingerprint area can disrupt the brush pattern and prevent accurate image capture. Excessive moisture in the finger can lead to fuzzy images. Environmental factors like dust, and humidity can affect sensor performance as well.

In general, the quality of fingerprint images depends on the sensor characteristics and user factors. By optimising sensor technology, ensuring appropriate user interaction, and possibly considering user-specific characteristics we can improve the quality of fingerprint images resulting in a more reliable and secure fingerprint recognition system.

By conducting a comparative analysis of fingerprints captured by two sensors which are a light-emitting sensor and an optical sensor, this project will provide insights into the quality of fingerprint images captured by two sensors and the influence of metadata on fingerprint images. Fingerprint quality is calculated using the NFIQ2 [1] assessment tool. Developed by the National Institute of Standards and Technology (NIST), The NFIQ tool is a widely used open-source software. NFIQ2 tool analyses images based on sharpness, contrast, and minutiae details such as completeness and accuracy of the ridges and branches of captured fingerprints which are key features for recognition.

2.1: Literature review:

The field of biometric recognition has kept on emphasising the importance of fingerprint image quality, given its direct impact on the accuracy and reliability of recognition systems. This review focuses on recent comparative studies and advancements in fingerprint image quality enhancements.

2.1.1: Influence of Metadata on Fingerprint Image Quality

Soabbe, Djara, and Vianou(2020)[4] offer a topology of metadata that influences the performance and security of biometric systems, indicating the importance of comprehensive metadata for accurate image analysis and system vulnerabilities. According to their paper, scars and marks such as tattoos are one of the physical aspects that affect biometric systems as well as volume, flash, brightness, noise, and temperature can affect the system's performance as well.

The authors of *"Fingerprint quality per individual finger type: A large-scale study on real operational data"* [5] did a detailed study on the quality of fingerprints across individual finger types using operational data. According to their research, not all fingers provide the same quality level as well as the dominant hand of the subject is expected to produce fingerprints of higher quality.

Samuel, Martin, and Magerand [2] researched more about verification failures in African election settings. Based on that the conclusion was Age, moisture on fingerprints and pressure can affect the quality of fingerprint images collected by light-emitting sensors. This research also mentions the proper placement of the fingertip showed a low-quality score as well dry fingertips have recorded better-quality of fingerprints compared to sweaty fingertips. Another important observation mentioned in this paper is thumb has better fingerprint quality compared to the index fingers.

2.1.2: Fingerprint Image Assessment and Evaluation

The comparative research from *"A comparative study of fingerprint image-quality estimation methods"* (2007) [8] paper looks at different fingerprint quality estimation methods which extract features of fingerprint images, such as Gabor filter responses, power spectrum and pixel intensity values to assess which metrics are most effective in quality determination. This study suggested that quality measures work differently for each sensor.

The authors of *"The Influence of Fingerprint Image Degradations on the Performance of Biometric System and Quality Assessment"* [6] conducted a study by degrading a fingerprint image by different degradation techniques to investigate how fingerprint image degradation influences the performance of the recognition system. They used NFIQ [1] to assess these images as it provides a standardized way to evaluate fingerprint image quality, which is vital for comparing the performance of different sensors and enhancement algorithms. This open-source software allows quality values to be tightly defined and then numerically calibrated, allowing for the standardisation needed to support the worldwide deployment of fingerprint sensors with universally interpretable image qualities. [7].

A paper by Olsen, Haiyun Xu, and. Busch [9] presents Gabor filters as potential quality measures for the NFIQ 2.0, suggesting enhancements to tools assessment capabilities. As Gabor filters are used to make changes in fingerprint images, they can also be used as a potential quality measure.

2.1.3: Fingerprint Sensors

There are sizable studies and discussions available on the productivity of different types of sensors. The idea behind choosing optical sensors and light-emitting sensors is that The paper named *"Review of Fingerprint Sensing Technologies"* [18] lists available fingerprint sensors available till 2008. It has mentioned the need for flexible, strong, and less environmentally sensitive fingerprint sensors. Also need to develop more sensitive and high-resolution fingerprint sensors that can capture detailed information from fingers with ridges and valleys.

Optical sensors have been in use for a long time, and there are a lot of studies and research available about them. But light-emitting sensors are relatively new with very limited research. The main documentation found on light-emitting sensors is by the manufacturing company of light-emitting sensors.

Optical fingerprint scanners are the oldest method of capturing fingerprints.[12] Optical fingerprint sensors generally use charge-coupled devices (CCD) or CMOS-based optical imagers to capture fingerprint images [11]. It then uses algorithms to detect unique patterns on the surface, such as ridges or valleys, by analysing the lightest and darkest areas of the images.[12] These sensors can capture high-quality contrast images but may face issues with varying finger conditions like dry fingers. As optical sensors are affected by light exposure like the sun, adjusting exposure times for accurate darkness levels is necessary to get a clear image. Optical sensors can be cost-effective, but environmental factors may influence the quality of fingerprint images. [11].

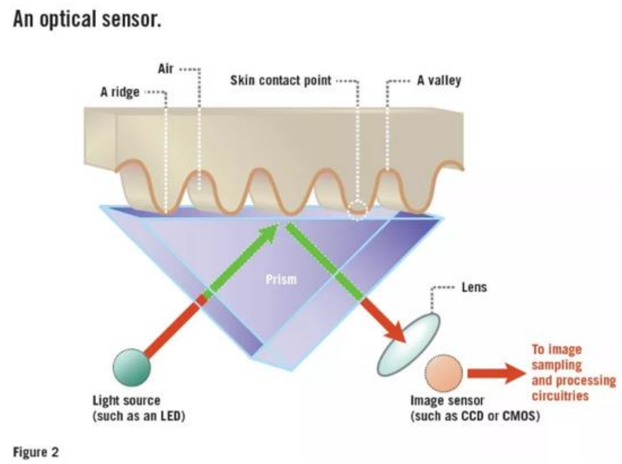


Figure 2:Inner working in Optical sensor [12]

Light Emitting Sensor (LES) technology in fingerprint scanning is a progressive approach that has been widely adapted for its potential to produce high-quality biometric data. LES technology offers an alternative by using a multilayer polymer composite that luminesces in the presence of an electric field, which is activated by ridges of the fingerprint when the finger is placed on the sensor.[13] This method is famous for collecting high-resolution fingerprint images. It is valued for its accuracy as it's not much affected by dry and wet fingers or black marks on the finger. There is no existing study available on how Light-emitting sensors work compared to other sensors. This study should be able to provide more insights on that.

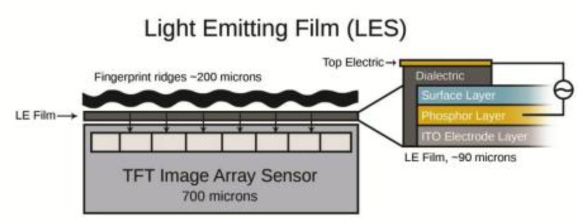


Figure 3:Inner working in Light-emitting sensor(LES)[13]

3 Specification

3.1.: Aim and objectives

This Project aims to increase our understanding of fingerprint image quality by evaluating and comparing the outputs from two different sensing technologies using the NFIQ2 tool. Furthermore, it aims to analyse how various metadata factors such as the subject's gender, hand preference and individual finger preference will impact the quality score for fingerprint images. This will help to understand what the best circumstances are to consider while collecting fingerprints so fingerprint images can have higher quality scores that can be achieved to make fingerprint recognition easier.

The project objectives are as follows:

1. Conduct a comparative analysis of fingerprint image quality between optical sensors and light-emitting sensors (LES) to understand which technology provides better quality for biometric authentication.
2. Examine how different metadata impacts the quality assessment of fingerprint images generated by both optical and light-emitting technologies, to find trends or biases in quality score.
3. Discover a set of ideal metadata (associated with fingerprints) that can help the quality assessment process, thereby improving the accuracy and reliability of both sensor technologies in real-world applications.

3:2.: Requirements

This project has various requirements. Technical requirements here contain databases and tools used for this project. I have used the MASIVE dataset which is collected using light-emitting sensors and SOCOFing which is collected using optical sensors. I have used the NFIQ2 tool which is a standard tool for fingerprint quality assessment developed by NIST (National Institute of Standards and Technology) for quality assessment of fingerprint.

There are also a few legal and regulatory requirements that need to be fulfilled for this project. Risk assessment and ethics assessment are two important assessments that need to be done to work on this project.

3.2.1.: Datasets

Biometrics information can very easily lead to the individual which raises lots of privacy concerns and a high standard of security is maintained while working with this data. This is a part of the reason there are limited published data sets available with fingerprint information. One of the aims of this project is also to find how metadata affects fingerprints, it made options for the right dataset very limited.

The reason behind choosing MASIVE as one of the datasets is it is collected by my supervisor which makes the data reliable also it comes with a lot of metadata information including environmental factors.

The idea behind choosing SOCOFing as another dataset for this research is this is publicly available and comes with metadata related to participants which made it the first choice.

Participants of MASIVE and SOCOFing belong to the African region, it was another point considered while selecting these datasets.

I have been trying to get access to more datasets for optical sensors. There is one more data set available with Chinese participants. Currently, I'm waiting for their approval of my application.

a. MASIVE Dataset

- This dataset contains fingerprint images of Nigerian volunteers, collected in Nigeria in operational settings that are similar to those of the National elections which are conducted outdoors.
- This dataset is collected using Light-emitting sensor (LES) technology.
- The scanner used to collect fingerprints is the Integrated Biometrics Columbo 500 PPI single fingerprint scanner.
- The age of participants is 18(inclusive) to 99 years.
- There are a total of 288 participants.
- This dataset includes 12,000+ fingerprint images.
- For all participants, the fingerprint images collected were the index fingers and thumbs for both hands in two different sessions.
- The dataset contains metadata related to gender, age, hand, finger type, occupation, physical conditions of fingers and environmental factors like humidity and temperature.
- This is an unpublished dataset.
- This dataset is available from the University of Dundee.

b. SOCOFing Dataset

- Sokoto Coventry Fingerprint Dataset (SOCOFing) is a fingerprint dataset designed for academic research purposes.
- This dataset is collected using Optical sensor technology.
- The scanners used to collect fingerprints are Hamster Plus (HSDU03PTM) and SecuGen SDU03PTM sensor scanners.
- The age of participants is 18 years and more.
- There are a total of 600 African participants.
- This dataset includes 6,000 fingerprint images.
- For all participants, the fingerprint images were collected for all fingers for both hands including the little finger, ring finger, middle finger, index finger and thumb of the left and right hand.
- The dataset contains metadata related to gender, finger type, and hand type.
- This is a published dataset.
- This dataset is available for all at the Kaggle.com website.

3.2.2: Risk assessment

According to GDPR(General Data Protection Regulation), biometric data is considered a special category of data as it can be used to identify an individual.[21] There are high levels of risks associated when working with biometric data.

- Fingerprint images are part of biometric data, there are lots of potential risks and vulnerabilities when it comes to data collection, storage, and usage. So, working with this kind of personal information involves a risk assessment process to rule out potential risks.
- Risk assessment form submission for approval is one of the important steps when it comes to working with biometric data.
- For this project main concerns were keeping data secure from unauthorised access, and misuse and keeping individual privacy and rights intact.

3.2.3: Ethics requirements

As fingerprint information is very sensitive and can lead to the identification of a person, some security prevention measures need to be followed while using these datasets.

Risk assessment involves listing out the potential risks and vulnerabilities to work on the project. To secure ethics approval, it is required what security measures will be taken to secure access and usage of data.

As the MASIVE dataset is published dataset, it is to be handled with all security and privacy measures in place.

Here I have explained some of the security measures taken to work with this data:

- All the process is supposed to be carried out on a university-managed passphrase-protected machine.
- Data should not be accessed in public places where It can be viewed by others.
- The data should not be accessed or sent to non-university systems or services. Off-campus access requires to use of MyDesktop a two-factor authentication to access the data on OneDrive.

Data will be erased after the Project has been examined and the machine used will be returned to the university.

3.2.4: NFIQ2- NIST (National Institute of Standards and Technology) Fingerprint Image Quality tool

There are multiple tools available out there for fingerprint quality assessment such as IQF(Image Quality of Fingerprint) software application[14] and VeriFinger which is a commercial SDK mainly used for fingerprint recognition rather than just quality assessment.[15]. I have decided to use NFIQ2 because it is developed by NIST and has relatively solid research support. Also, it uses a machine learning approach to directly link image quality metrics to the accuracy of fingerprint-matching algorithms.

- NFIQ2 is an open-source software that links the image quality of optical and ink 500 PPI fingerprints to operational recognition performance. This allows quality values to be tightly defined and then numerically calibrated, which in turn allows for the standardization needed to support a worldwide deployment of fingerprint sensors with universally interpretable image qualities.
- NFIQ2 quality features are formally standardised as part of ISO/IEC 29794-4 and serve as the reference implementation of the standard. It quantifies the quality of fingerprint images by scoring them between 0 and 100, with higher scores indicating images of higher quality that are expected to perform better in recognition systems. [1]
- NFIQ2 considers a variety of image characteristics, such as sharpness, contrast, and the presence of minutiae, which is vital for correct fingerprint identification.
- NFIQ2 is trained on a random forest algorithm which is operated by constructing multiple decision trees during training and outputting the class that is the mode of the classes for classification, and mean prediction of the individual trees for regression.

3.3.: Project plan and schedule

The Gantt chart from Figure 4 shows an 11-week project plan, with tasks.

This chart uses colour coding to indicate the status of each task: Predicted (Actual Plan), On time (Acceptable timeline), delayed (Behind schedule).

I have spent week one understanding the project concept and started figuring out which sensors and datasets I will use. The next step was risk assessment and ethics approval. The important thing to notice from the above chart is that there was a six-week delay in getting ethics approval, which delayed the other tasks related to the comparison of quality score results for both datasets and which in turn left us with a very short time to work on analysis and enhancements.

In that six-week delay, I was working on the literature review as well as trying to find alternative datasets and getting access to them. I have spent a lot of time understanding NFIQ2, its inner workings and applications. Also, I have done some experiments with image enhancement with SOCOFing images.

I received ethics approval in week 9, which left me with 2 weeks for data analysis, comparison, and documentation.

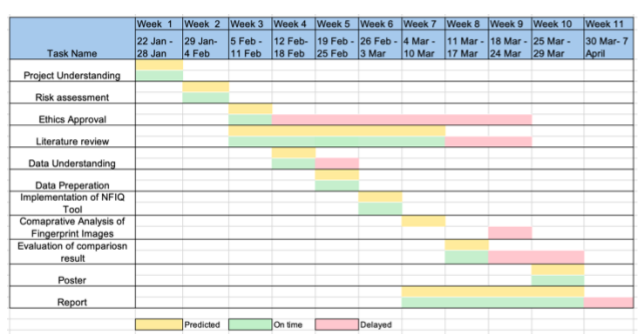


Figure 4. Project Plan

4 Design

Here in this project, I referenced the data-driven approach and waterfall model together.

4.1: Data-driven approach:

A data-driven approach is necessary for this project as it helps with objective analysis and comparison of fingerprint image quality. This approach makes sure that conclusions and related recommendations are based on quantifiable data which is critical for the development of a more accurate, robust and reliable biometric system.

Here a data-driven approach would involve a strict method of collecting, processing, and analysing large sets of fingerprint images to drive conclusions about the quality assessment of different sensor technologies. It starts with a robust collection of data from pre-defined datasets. Next, pre-processing strategies to clean and normalize the data are applied, ensuring consistency across various image qualities and formats. The core of the approach then uses this prepared data to feed into the NFIQ2 tool, which analyses and assigns quality scores based on specific features of the fingerprint images. These scores and their corresponding metadata are then statistically analysed to identify patterns and insights that inform the project objectives. The conclusions drawn from this analysis directly influence the decision-making process, such as selecting sensor technologies or adjusting image capture techniques to enhance quality.

Figure 5 shows the entity relationship diagram of the data involved in this project. Participants and fingerprint images are the main entities in this project. Data related to the participant entity have participant ID, gender, hand, and finger type. Data related to fingerprint images have participant ID, filename, quality score, resolution, Uniform image score, Empty Image Or Contrast too low score, Count of Minutiae in fingerprint images and Sufficient Fingerprint Foreground score.

Based on these attributes, results and conclusions will be calculated.

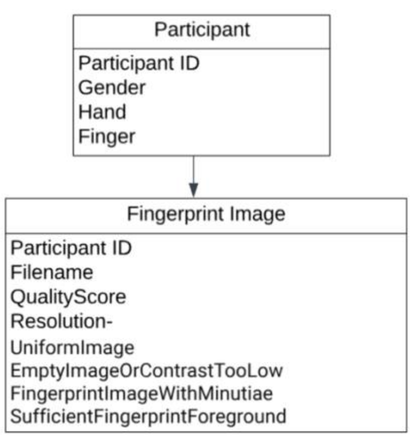


Figure 5. Entity Relationship Diagram

4.2.: Waterfall Model

Figure 4 shows all the steps and different phases considered in this project. As we can notice, the plan follows a sequential approach means each step after another. All the steps must be decided before in planning phase. This model offers a clear view, a structured process with detailed stages and objectives helps in better understanding and management.

This model is not very flexible for unexpected issues and roadblocks. Figure 4 shows, that ethics approval and access to data have been the biggest roadblock for this project. Only after getting access to the dataset main work of the project was started.

The below flowchart shows the main steps considered in this project which are data collection, image processing to provide it as input to NFIQ2, and later cleaning the output of NFIQ2. After that analyse data and gather conclusions with the help of data analysis and data visualization.

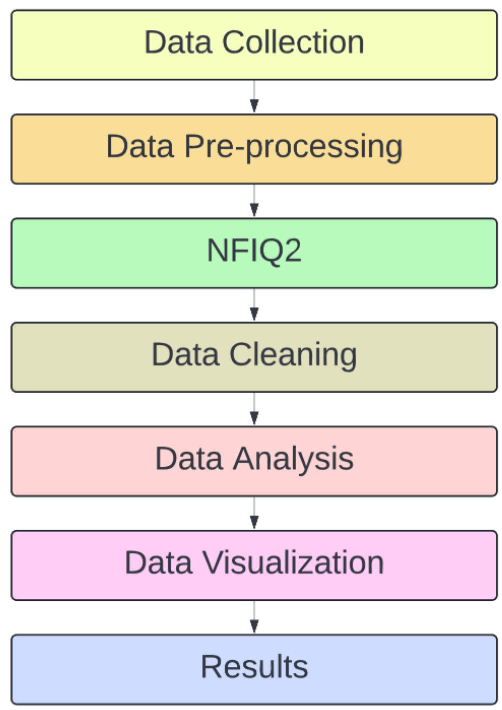


Figure 6: Flow chart

5 Implementation and Testing

In this section, all steps in implementation are explained in detail. Here I have considered data collection, data pre-processing, NFIQ2 evaluation and data cleaning as part of the implementation of the project.

5.1.: Data Collection:

For security and privacy purposes individuals, fingerprint datasets are not usually available publicly and there are very limited datasets available with metadata information. These two datasets were selected for this project.

- MASIVE: This dataset is collected by light emitting sensor (LES) technology. As it is an unpublished dataset, it is required to get ethics approval from the Ethics Committee of the University of Dundee to access this dataset.
- SOCOFing: This dataset is collected using Optical sensor technology. This is a published dataset available at the University of Dundee.

5.2.: Data pre-processing:

Fingerprint images need to be prepared into an acceptable input format for NFIQ2 to assess the quality of these images.

For Pre-processing, I have used The Python Imaging Library (PIL) for Python programming language that helps to play around with images. PILOW library is used to make all image-related changes. It is a very well-known library for manipulating images. Here are some pre-processing steps that need to be taken as follows:

- **Resolution Adjustment:** As recommended by NFIQ2, the image resolution should be 500 PPI (Pixels Per Inch). Fingerprint images from the MASIVE dataset already have a resolution of 500 PPI. Fingerprint images from SOCOFing have image resolution ranging from 72 PPI to 96 PPI. To convert these images into the recommended resolution by NFIQ2, the PPI needs to be increased from 72 PPI to 500 PPI. The formula to calculate PPI is as follows:

$$\text{PPI} = \frac{\text{Pixel Dimension}}{\text{Physical Dimension in inches}}$$

If the image doesn't have metadata default PPI used is 72 which is common for digital images.

The below sample python function shows how the PPI is increased to 500 for SOCOFing images.

```
def resize_image_to_500_ppi(image_path):
    expected_ppi = 500
    with Image.open(image_path) as img:
      # calculate the current physical size in
inches.
     # Using 72 PPI as default if PPI is not set
     current_width_in_inches = img.width /
img.info.get('dpi', (72, 72))[0]
      current_height_in_inches = img.height /
img.info.get('dpi', (72, 72))[1]
# Calculate the new dimensions in pixels for
the expected PPI
      new_width =
int(current_width_in_inches * desired_ppi)
      new_height =
int(current_height_in_inches * desired_ppi)

      # Resize the image to the new
dimensions
      resized_image = img.resize((new_width,
new_height), Image.ANTIALIAS)
     return resized_image
```

Image dimension for SOCOFing images **before**:

Image dimensions: 96 x 103 pixels

Image dimension for SOCOFing images **after**:

Image dimensions: 500 x 537 pixels

- **Image Format Conversion:** NFIQ2 needs images in BMP, PNG, and other compatible formats. Both datasets have images in BMP format, still, there was an issue with processing fingerprint images from SOCOFing. So, I had to try changing the format to make it work and convert it to PNG. Below sample Python function below shows how to convert the images with the BMP extension in one folder to images with the PNG extension.

```
def convert_bmp_to_png(input_folder,
output_folder):
   # Create the output folder if it doesn't exist
   if not os.path.exists(output_folder):
      os.makedirs(output_folder)

   # Get a list of all BMP files in the input folder
   bmp_files = [file for file in
os.listdir(input_folder) if
file.lower().endswith('.bmp')]
   # Iterate through each BMP file and convert to
PNG
   for bmp_file in bmp_files:
      # Construct the full path for input and output
images
      input_path = os.path.join(input_folder,
bmp_file)
      output_path = os.path.join(output_folder,
os.path.splitext(bmp_file)[0] + '.png')

      # Open the BMP image and save as PNG
      with Image.open(input_path) as img:
           img.save(output_path, format='PNG')
```

- **Grayscale Conversion:** NFIQ2 does not process colour information, so it is required to convert colour images to 8-bit grayscale. Fingerprint images collected by MASIVE were in grayscale format. For SOCOFing, I had to change the format from colour to grayscale. Below is a sample Python function to change the colour scale of fingerprint images.

```
def convert_to_grayscale(image_path):
   with Image.open(image_path) as img:
      # Convert the image to grayscale
      grayscale_image = img.convert('L')
     return grayscale_image
```

NFIQ2 supports batch processing. The input file for batch processing is supposed to be in text format with the path of all images that are supposed to be processed.
Below sample Python code below shows how to get all image names in the same folder. As all the SOCOFing images were in the same folder, Below code snippet below was used to get all filenames in one text file.

```
IMAGE_DIRECTORY =
"C:/Users/2544403/Downloads/SOCOFing_altered_
png"
OUTPUT_FILE =
"C:/Users/2544403/Downloads/altererd_image_nam
es.txt"
image_files = [f for f in
os.listdir(IMAGE_DIRECTORY) if
f.lower().endswith((".png", ".jpg", ".jpeg", ".gif",
".bmp"))]
# Write image names to the output file
with open(OUTPUT_FILE, 'w') as file:
    for image_file in image_files:
        file.write(
"C:/Users/2544403/Downloads/SOCOFing_altered_
png/" + image_file + '\n')
```

For the MASIVE dataset, the folder hierarchy was like this:

(Main folder) -> (Session 1 or 2) -> (participants ID) -> (Impression ID) -> (fingerprint Images)

Below is the code snippet to get image file names from the above hierarchy to a single text file for one session in a text file to provide as input for NFIQ2

```
def extract_file_names(folder_path):
    file_names = []
    # Walk through each directory and subdirectories
    for root, dirs, files in os.walk(folder_path):
        # Iterate through files in the current directory
        for file in files:
            # Append the absolute file path to the list
            file_names.append(os.path.join(root, file))
    return file_names

 # Replace 'folder_path' with the path to your folder
containing multiple folders
folder_path =
r'C:\Users\2544403\Downloads\images_and_metada
ta\images_and_metadata\session_2'

# Extract file names from the specified folder
file_names = extract_file_names(folder_path)

# Write the list of file names to a text file
output_file_path =
r'C:\Users\2544403\Downloads\MASIVE_session2.t
xt'
with open(output_file_path, 'w') as f:
    for file_name in file_names:
```

5.3.: NFIQ2

NFIQ2 is not usually installed like a software package. It might need to be complied with from the source code provided by NIST. This is the link where the source code can be found.
https://github.com/usnistgov/NFIQ2/releases

Below I have explained some metrics NFIQ2 uses in the random forest algorithm to assign quality scores.

- OCL - Orientation certainty level
  This measures the consistency of the orientations of ridges and valleys contained in the local region of the fingerprint image
- LCS - Local clarity score
  This measures the ridge and valley structure clarity based on the thickness.
- FDA - Frequency domain analysis
  This measures the frequency of sinusoids following ridge valley structures.
- RVU – Ridge valley uniformity
  This measures the consistency of the ridges and valley widths.
- OFL – Orientation flow
  This measures the ridge flow continuity which is based on the absolute orientation difference between a block and its 8-neighbourhood.
- MU- Arithmetic mean of pixel values
  This measures the arithmetic mean of the grey scale of pixels in the input image.
- MMB – Mean of block mean intensities
  This measure is the arithmetic mean of per block computed arithmetic mean in the grey scale of input images.
- MIN-CNT – Minutiae count in finger image
  This measures the total count of minutiae as in specific features of fingerprint images.
- MIN-COM – Minutiae count in centre of mass region
  This measures the minutiae count in the local area of the fingerprint image region.
- COH – ROI orientation map coherence sum
  This measures the coherence map of the orientation field.
- COH-ROI relative orientation map coherence sum
  This measure computed the relative orientation map coherence sum.
- AREA- Region of image means
  This measures the mean of total pixels computed.

Once it is installed and complied with, we can run it from the command line to evaluate fingerprint images.
The below figure shows how we can run it using the command line and currently available flags as well as version information of the dependent libraries used by NFIQ2.

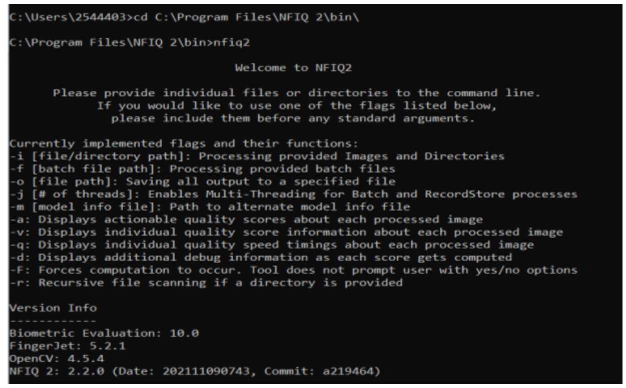
As per image shows, I have used NFIQ2 with version 2.2.0 for this project. Libraries used in the NFIQ2 tool are Biometric Evaluation with version 10.0, FingerJet which is an opensource minutiae extraction library with version 5.2.1 and OpenCV which is an opensource computer vision and machine learning software library with version 4.5.4.

There are 11 different flags available to use for NFIQ2.

- -i: This flag is used to process a single image as input followed by the path of the image.
- -f: This flag is used to process a batch of images as input. All image names are supposed to be put in a text file and the path of the file is followed the flag.
- -o: This flag is followed by the output file path which is supposed to be in CSV format to store the output of the NFIQ2 assessment.
- -j: This flag is used for multithreading for batch processing, but for these datasets, it only took a few minutes to process I decided not to use this.
- -m: This flag is used to specify the path to the model directory NFIQ2 that should be used for computing the quality score. By default, NFIQ2 uses a random forest algorithm, it is possible to use different models which are supposed to be stored in a file with the extension '.dat'. Because of the time constraints, I was unable to spend more time playing around with the flag.
- -a: This flag will show a numerical score ranging from 1 to 100 for input fingerprint image/s.
- -v: This flag shows individual quality score information about each processed image such as minutiae count, contrast, and uniformity of images.
- -q: This flag shows time to come up with individual quality scores. As in this project, we are more concerned about comparing quality instead of processing speed, I did not find this output data important to research. So, I decided not to use this.
- -d: This flag shows debug information for each score computed.
- -F: This flag forces computation to occur without prompting on the command line for user input. In the case of single images, it is fine to provide input. But while batch processing, software directly returns an error, so I decided to use this one.
- -r: This flag is used for recursive file scanning if a directory is provided. There was a need to use it for this project.

Here is the exact command I used on the command line to process images from datasets.

```
nfiq2 – f input.txt -o output.csv -a -v -F
```



```
C:\Users\2544403>cd C:\Program Files\NFIQ 2\bin\

C:\Program Files\NFIQ 2\bin>nfiq2

                    Welcome to NFIQ2

    Please provide individual files or directories to the command line.
         If you would like to use one of the flags listed below,
           please include them before any standard arguments.

Currently implemented flags and their functions:
-i [file/directory path]: Processing provided Images and Directories
-f [batch file path]: Processing provided batch files
-o [file path]: Saving all output to a specified file
-j [# of threads]: Enables Multi-Threading for Batch and RecordStore processes
-m [model info file]: Path to alternate model info file
-a: Displays actionable quality scores about each processed image
-v: Displays individual quality score information about each processed image
-q: Displays individual quality speed timings about each processed image
-d: Displays additional debug information as each score gets computed
-F: Forces computation to occur. Tool does not prompt user with yes/no options
-r: Recursive file scanning if a directory is provided

Version Info
------------
Biometric Evaluation: 10.0
FingerJet: 5.2.1
OpenCV: 4.5.4
NFIQ 2: 2.2.0 (Date: 202111090743, Commit: a219464)
```

Figure 7: NFIQ on the command line

After executing this command on the command line quality score report by NFIQ2 will be stored in the output.csv file.

```
MASIVE_Session1_df["image_name"]=MASIVE_Session1_df["Filename"].str.split('\\',n=6).str[6].str.replace('\\','_')
MASIVE_Session1_df["participant_id"]=MASIVE_Session1_df["image_name"].str.split('_',n=3).str[2]
MASIVE_Session1_df["session"]=MASIVE_Session1_df["image_name"].str.split('_',n=2).str[1]
MASIVE_Session1_df["impression"]=MASIVE_Session1_df["image_name"].str.split('_',n=5).str[4]
MASIVE_Session1_df["hand"]=MASIVE_Session1_df["image_name"].str.split('_',n=7).str[5]
MASIVE_Session1_df["finger"]=MASIVE_Session1_df["image_name"].str.split('_',n=7).str[6].str.split('.',n=1).str[0]

metadata1_df['participant_id']="DIN" + metadata1_df['DIN'].astype(str)
MASIVE_df=pd.merge(MASIVE_Session1_df,metadata1_df,on="participant_id")
```

5.4.: Data Cleaning

For this project, I'm using Pandas which is considered an essential library in the Python Data Science stack, as it can handle and manipulate large amounts of data easily.

After importing output files for both databases, for data cleaning, I removed unnecessary columns. Also, there was an error in processing a few images in both datasets, rows with null values for the quality score, so I removed them.

This is the sample code snippet for the above:

```
df.info()
df.dropna(subset = ['QualityScore'], inplace = True)
df = df[['Filename', 'QualityScore', 'UniformImage',
'EmptyImageOrContrastTooLow',
'FingerprintImageWithMinutiae',
'SufficientFingerprintForeground']]
```

Later, pandas extracted metadata such as gender, finger type, and hand type from the filename.
Here are code samples for those.

```
SOCOFING_df["image_name"]=SOCOFING_df["Filename"].str.split('/',n=5).str[5]
SOCOFING_df["participant_id"]=SOCOFING_df["image_name"].str.split('_',n=2).str[2]
SOCOFING_df["gender"]=SOCOFING_df["image_name"].str.split('_').str[2]
SOCOFING_df["hand"]=SOCOFING_df["image_name"].str.split('_').str[3]
SOCOFING_df["finger_type"]=SOCOFING_df["image_name"].str.split('_').str[4]
```

6 Evaluation and/Testing

The evaluation part of this project consists of data analysis and data visualization. I have used Python libraries like pandas, NumPy, matplotlib, seaborn, and pillow for data analysis using Jupyter Notebook as a platform. For Data visualisation, I have used PowerBI as a tool.

6.1: Data Analysis

Here figure 8 shows the statistics summary of the MASIVE dataset and Figure 9 shows the statistics summary for the SOCOFing dataset. The minimum quality score for fingerprint images from the MASIVE dataset is 0 and 16 for SOCOFing. Maximum quality score for fingerprint image is 95 and 72 is for SOCOFing. The average quality score for MASIVE images is 60.78 and 45.54 for SOCOFing. From this, we can conclude fingerprint images collected by light-emitting sensors have better fingerprint quality compared to images collected by optical sensors.
Uniformity in image, empty image or contrast level, total count of minutiae(features in fingerprint image such as bifurcations, closed loops) and Sufficient fingerprint foreground are some of the other values that affect. Fingerprint images.

	QualityScore	UniformImage	EmptyImageOrContrastTooLow	FingerprintImageWithMinutiae	SufficientFingerprintForeground
count	6887.00	6887.00	6887.00	6887.00	6887.00
mean	60.78	68.23	192.88	53.43	80165.44
std	21.37	9.21	23.04	36.84	22134.70
min	0.00	22.08	100.28	6.00	11962.00
25%	49.00	62.90	178.34	34.00	66191.50
50%	67.00	69.92	193.84	44.00	80557.00
75%	77.00	74.70	209.35	60.00	94774.50
max	95.00	109.51	251.03	255.00	197706.00

Figure 8: Statistics summary of the MASIVE dataset

	QualityScore	UniformImage	EmptyImageOrContrastTooLow	FingerprintImageWithMinutiae	SufficientFingerprintForeground
count	5954.00	5954.00	5954.00	5954.00	5954.00
mean	45.54	96.50	148.50	44.38	168425.54
std	7.07	6.50	22.86	24.33	28244.08
min	16.00	60.48	40.57	6.00	20060.00
25%	41.00	93.24	136.11	28.00	152931.25
50%	46.00	97.23	149.79	38.00	168733.00
75%	50.00	100.66	164.11	54.00	185025.75
max	72.00	118.32	226.43	252.00	268500.00

Figure 9: Statistics summary of the SOCOFing dataset

For the SOCOFing dataset, Figure 10 shows the fingerprint image with the highest quality score, 72 and Figure 10 shows the fingerprint image with the lowest quality score which is 16.
Because of privacy and security reasons, I'm not allowed to share images from the MASIVE dataset here. But from my observations, I can say fingerprint images in MASIVE have fingerprint placement for the SOCOFing dataset is not correct. Most of the images are in corners with some parts of the image getting cropped which might have affected to quality score of fingerprint images.

Attribute values for Images with the highest score and lowest score for MASSIVE and SOCOFing are in below table 1.

Minutiae are features of fingerprints such as bifurcation, and loops. After referring to Table 1 we can see images with high-quality scores have a lower count of minutiae compared to images with low-quality scores, for both datasets.
Furthermore, images with low-quality scores have a low value for Empty Image as in larger part of the image is not empty. That means the larger the empty part lowers the score.

Figure 10: Fingerprint with highest quality score in SOCOFing

Figure 11: Fingerprint with lowest quality score in SOCOFing

Attribute/Dataset	MASSIVE		SOCOFing	
	Highest	Lowest	Highest	Lowest
Quality Score	95	0	72	16
Uniform Image	77.50	58.52	92.47	118.32
Empty Image Or Contrast Too Low	163.72	137.60	168.16	122.49
Fingerprint Image With Minutiae	68	255	25	47
Sufficient Fingerprint Foreground	99164	134448	147417	153212

Table 1: Comparison of Attributes between MASSIVE and SOCOFing Image

	QualityScore	UniformImage	EmptyImageOrContrastTooLow	FingerprintImageWithMinutiae	SufficientFingerprintForeground
QualityScore	1.000000	-0.276749	0.285560	-0.251339	-0.227588
UniformImage	-0.276749	1.000000	-0.793384	-0.163089	0.780165
EmptyImageOrContrastTooLow	0.285560	-0.793384	1.000000	-0.069462	-0.793774
FingerprintImageWithMinutiae	-0.251339	-0.163089	-0.069462	1.000000	-0.024061
SufficientFingerprintForeground	-0.227588	0.780165	-0.793774	-0.024061	1.000000

Figure 12: Correlation Matrix for MASSIVE and SOCOFing combine

Figure 12 shows the correlation matrix for both MASIVE and SOCOFing images. As per that Quality, the score is positively related to EmptyImageOrContrastTooLow. For the rest of the attributes, UniformImage, FingerprintImageWithMinutae and SufficiantFingerprintForeground, the Quality score is negatively correlated.
Also, here we can see that UniformImage and SuffuciantFingerprintForeground have a 78% positive correlation which means if one of these has a high value of other will have a high value as well.
Next UniformImage and EmptyImageOrContrastTooLow have a 79% Negative correlation, indicating if one value is higher other value will be low.

6.2: Data Visualization

Data Visualisation and presentation are very important parts of the data-driven decision-making process. Here I've created some graphs using powerBI to further visualise the results of NFIQ for MASIVE and SOCOFing dataset fingerprint images.
Here figure 13 shows a bar graph representation of the quality score distribution for fingerprint images of MASIVE and SOCOFing datasets. As we can see fingerprint images from the MASIVE dataset have higher quality scores compared to images from SOCOFing.
For SOCOFing fingerprint images, quality score distribution is mostly focused from 30-60 and for MASIVE it is mainly focused from 60-90 which clearly states MASIVE has higher quality images.

Figure 13: Quality score distribution for MASIVE and SOCOFing

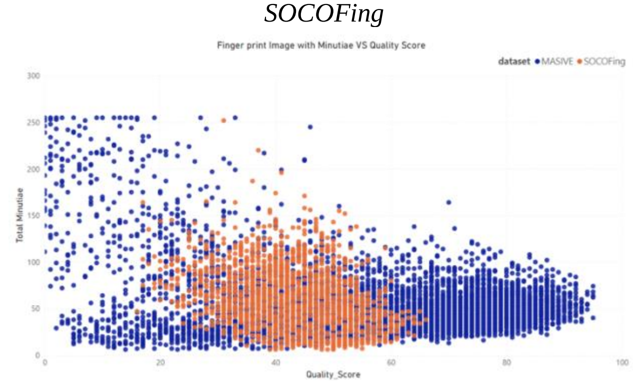


Figure 14: Count of minutiae to Quality Score

Figure 14 is a scatter plot representation of the total minutiae count for the quality score. In this graph, each dot represents one image. As minutiae refer to features of fingerprint images, my previous assumption was higher minutiae count would lead to more unique features which would affect the quality score to increase. But as we can see from the graph below graph and referring to the correlation matrix from Figure 11, it is confirmed that a higher minutiae count will not always result in higher quality scores.

Uniform Image score means ridge and valley consistency. Figure 15 shows a visual representation of each fingerprint image concerning the uniformity of ridges and valleys in the fingerprint image. This graph shows that the Uniform Image score of SOCOFing images is higher compared to MASIVE images.

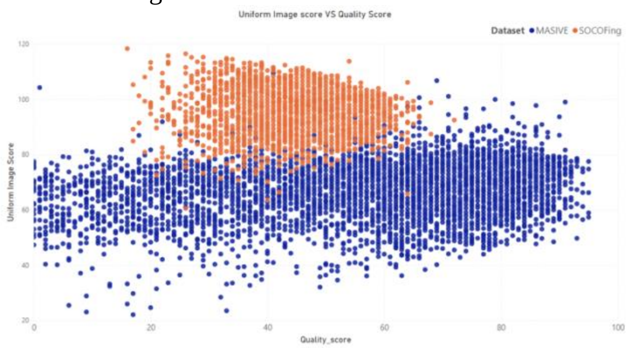


Figure 15: UniformImage score to Quality score

Empty Image or Contrast too low score as in a measure of grey levels of the image. Figure 16 shows an Empty Image and Contrast Too Low score to a quality score. It clearly shows fingerprint images from SOCOFing have low scores as in large part of the images are empty and for images from MASIVE, the value of the score is higher meaning these images have high grey-level content.

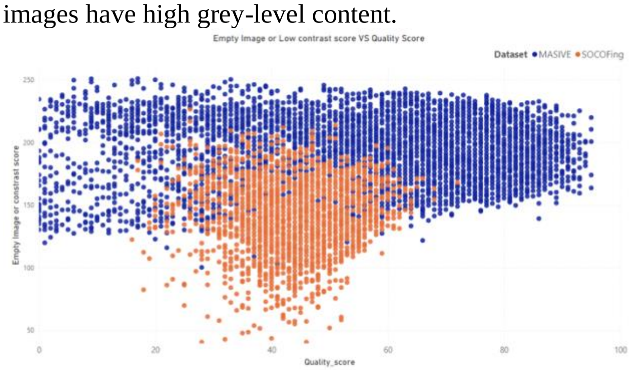


Figure 16: Empty Image or Contrast too low for Quality score

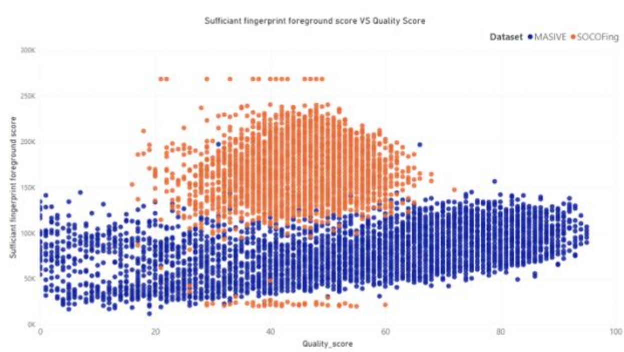


Figure 17: Sufficient foreground score to Quality score

Here Figure 17 shows sufficient foreground score to quality score. This number represents the number of pixels in the computed foreground as in the image.

SOCOFing fingerprint images have a large number of pixels computed in the foreground compared to MASIVE fingerprint images.

Figure 18 shows the quality score distribution for each hand for SOCOFing and Figure 19 shows the quality score distribution for each hand for MASIVE. As we can from both graphs left-hand has slightly better quality fingerprint image quality compared to the right-hand for MASIVE and SOCOFing.

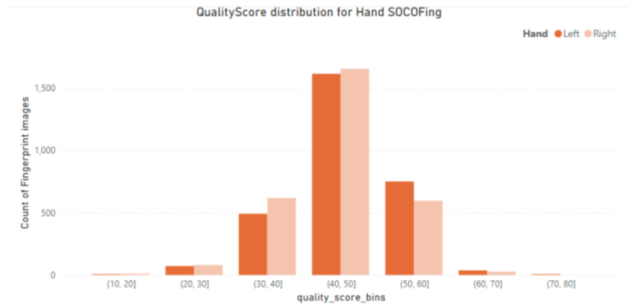


Figure 18:Quality score distribution of each hand for SOCOFing

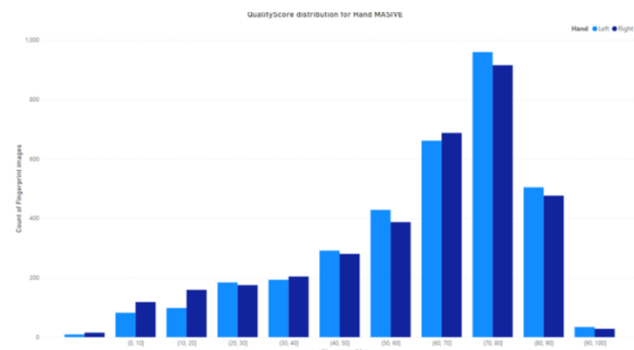


Figure 19: Quality score distribution of each hand for MASIVE

Figure 20 shows the quality score distribution of the index and thumb fingers for SOCOFing, and Figure 21 shows the quality score distribution of the index and thumb fingers for MASIVE.

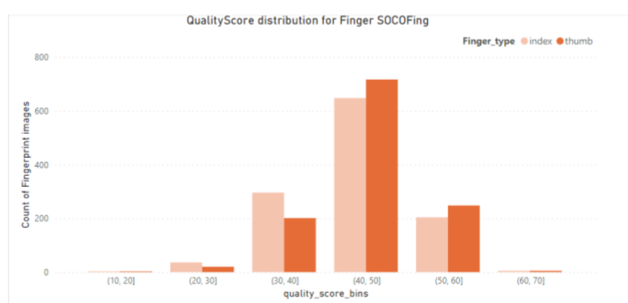


Figure 20: Quality score distribution of each finger for SOCOFing

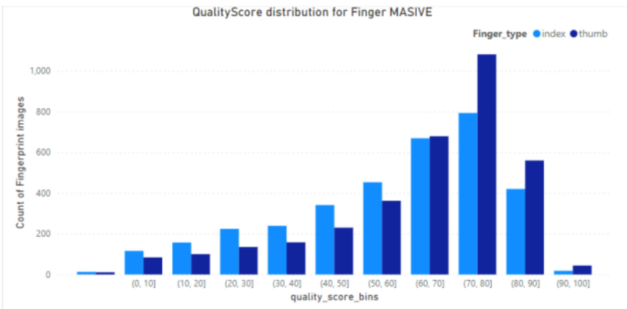


Figure 21: Quality score distribution of each finger for MASIVE

SOCOFing has fingerprint images of all fingers but as I'm doing a comparison here it made more sense to compare the fingers which are available for MASIVE as well. As we can see fingerprint images of the thumb have better quality compared to index fingers for both datasets.

Gender/ Dataset	MASIVE	SOCOFing
Male	60.42	45.88
Female	61.14	45.46

Table 2: Average Quality score per gender for each dataset

Table 2 shows the average quality score for each gender, male and female for MASIVE and SOCOFing datasets. For both datasets, the difference between both genders is barely more than 1. This suggests gender of the participant does not affect the quality of fingerprint images.

6.3: Fingerprint Image Enhancement

There are multiple techniques available to make changes in images like blur effect, increase contrast, removing noise, and image smoothening. I have done some experiments like this using Gabor filters. I'm able to increase the quality of one image at a time with specific values for parameters of Gabor filters. I am facing issues in coming up with techniques to change these values based on the image. I believe this will need some involvement in a deep learning model. Because of the short time in hand, I couldn't spend more time on that. So, I decided to use the existing library for fingerprint enhancement available at Git Hub.[17] The code here is a Python representation of work done in a paper by Hong L, Wan Y and Jain A, K.[16]. They have used oriented Gabor filters to enhance fingerprint images. The orientation of the Gabor filters is based on the orientation of the ridges and valleys. The shape of the Gabor filter is based on the frequency and wavelength of ridges and valleys as well.
Below I have attached two images to show how this code will change the fingerprint image after applying Gabor filters which leads to an increased quality score.

Figure 22: Original fingerprint image

Figure 23: Fingerprint image after applying Gabor filters

Here figure 22 represents the original fingerprint image and Figure 23 represents the fingerprint image after applying the Gabor filter from the fingerprint_enhancer library.
Table 3 shows the change in quality score post applying Gabor filters. 78.53 % time applying Gabor filters led to an increased quality score and 21.47 % time it led to a decrease in quality score.

Difference in Enhanced image Quality score and Original Quality score	Count of fingerprint images	Percentage
-30 to -20	1	0.02 %
-20 to -10	113	1.90 %
-10 to 0	1164	19.55 %
0 to 10	2717	45.63 %
10 to 20	1656	27.81 %
20 to 30	275	4.62 %
30 to 40	27	0.45 %
40 and above	1	0.02 %

Table 3: Tabular representation of change in quality score of SOCOFing fingerprint images

Figure 24:SOCOFing image with the highest decrease in Quality score before enhancement

Figure 25:SOCOFing image with the highest decrease in Quality score after enhancement

Figure 24 shows a SOCOFing fingerprint image with a quality score of 53 before applying the fingerprint enhancement technique which after processing decreased to 29 by NFIQ2 as shown in Figure 25.

Figure 26:SOCOFing image with the highest increase in Quality score before enhancement

Figure 27:SOCOFing image with the highest increase in Quality score after enhancement

Figure 26 shows a SOCOFing fingerprint image with a quality score of 27 before applying the fingerprint enhancement technique which after processing increased to 71 by NFIQ2 as shown in Figure 27.

Based on the above analysis, I have come up with several observations and conclusions which are discussed in a later section.

7 Limitations

Data quality as in fingerprint image quality has been one of the main limitations of this project. Acquiring fingerprint images of good quality was very difficult for optical sensors.
MASIVE has fingerprint images of two fingers that are index and thumb while SOCOFing has fingerprint images of all fingers. Because of this, I was only able to do a comparison between two fingers instead of all fingers.

8 Description of the final product

This is a data-driven research-based project focused on gaining more understanding of fingerprint images collected by two different sensors, rather than a product. Findings from analysing the quality of these fingerprint images will help us understand how metadata affects fingerprint images and what are the best circumstances to get the highest quality fingerprint so it can help with fingerprint recognition further helping with biometric security.

9 Appraisal

For this project securing ethics approval took a lot of time. Next time when I'm dealing with biometric information, I'll try to focus on speeding up the ethics approval process.
While working with the SOCOFing dataset, I found that the quality of fingerprint images is very poor compared to MASIVE fingerprint images. I believe to some extent this would have affected the analysis as well and getting access to good quality and reliable datasets is very important for biometric research to get unbiased comparison. Next time I would like to get my hands on more reliable data sources so unbiased comparison can be done on this project.
I have spent quite some time studying and experimenting with image enhancement techniques for fingerprint images. However, because of delays in the original project plan and pressing deadlines, I had to shift my focus towards the documentation of the project. If I get a chance again, I would like to give more attention towards enhancing the fingerprint image quality of low-quality datasets.
As the main goal of this project was to compare fingerprint images collected from two different datasets, I should have tried to work with fingerprint data which was collected by different sensors for the same participant and similar environmental circumstances to get optimal results.
With the current analysis I have done, I can say the Light-emitting sensor has better quality when to the resolution of fingerprint images. Also, optical sensors can be affected by environmental conditions such as light. It is not mentioned anywhere under what environmental conditions SOCOFing images are collected, in future, I would like to take that under consideration as well.
Due to privacy and security reasons, I'm not able to share sample MASIVE images, but one thing I did notice looking at those images is finger placement on the scanner while collecting fingerprints. In MASIVE fingerprint images, one can see more fingerprint area as compared to SOCOFing

fingerprint images where fingerprint images can be mostly seen at corners of images, they are not placed correctly on the scanner.
I was able to find trends for hand and finger. The above analysis suggests that the left hand has a higher chance of producing quality images compared to the right hand.
Also, it concludes thumb fingerprint images result in higher quality images compared to index finger images.

10 Summary and Conclusions

The conclusion drawn from the above analysis is that the light-emitting sensors are better at capturing high-resolution images which helps in high-quality scores compared to optical sensors.
Fingerprint images from the SOCOFing Dataset need a lot of refining to be accepted by NFIQ2 quality standards in terms of colour scale, format, and resolution.
For both sensors, the Left-Hand finger shows a higher quality score compared to the right hand.
Fingerprint minutiae are the minute features of friction ridge skin that make the forensic use of fingerprint identification possible. But a higher minutiae count does not mean the quality score will be high as well.
Finger placement while capturing fingerprint is very important as well. Most of the fingers from SOCOFing images have cropped fingerprint images situated at the corners of the image which means the finger wasn't placed correctly on scanners. This can affect sufficient foreground parameters checked by NFIQ2 which is why it is a very important thing to consider while collecting fingerprints.
Also, low contrast in the images may lead to a low grey scale, which eventually increases the empty area in the image. Most of the SOCOFing images have low empty images and contrast too low, which might be the result of fingerprint placement and natural light available while capturing the fingerprint.
Thumb Fingerprints have high-quality scores in both datasets compared to other fingers same as the research done by Samuel, Martin and Magerand [2].
The gender of the participant does not affect the quality of fingerprint images.

11 Future work

Biometrics of a person can be used to identify the individual. Because of the privacy and security of an individual and to follow GDPR(General Data Protection Regulation), there are rarely any fingerprint image datasets available for research purposes. In future, I would like to access a dataset of optical sensor images with more metadata such as environmental conditions like temperature and humidity, also participants' fingers are scarred. Also, information about is the participant most regularly used as in the dominant hand. If possible, I would like to get this data for the same participant using both sensors under the same environmental conditions so I can compare each finger with its other version collected by different sensors. This comparison should give optimal results.
There is one more dataset available of fingerprint images collected using an optical sensor known as CASIA Fingerprint Image Database which has more than 20,000 images of 500 participants. It contains metadata such as hand and finger type [22]. It took a lot of time to get approval for this dataset as well. I received approval from the authors in week 11 which was quite late, so I didn't get a chance to work with this dataset. In future, I would like to do more experiments and analysis with data and compare these images with the MASIVE dataset to check if the conclusions of the current analysis will change or not.
Next, I would like to use different tools and techniques to enhance the fingerprint images to evaluate accuracy. In this project I have used NFIQ2, in future I would like to use other tools like Verifinger, and IQF. In NFIQ2, the metrics and their respective threshold values for quality scores are already defined. I haven't done any experiments by changing those values yet, but I would like to try different threshold values and how they affect the quality score.
I have done some experiments with Gabor filters so far and tried to refer to existing research [16] and Python code implementation of the fingerprint enhancer library[17]. It helped a bit with the quality scores of a few images. I added details about that evaluation section. I would like to do more experiments with this work for more enhancements.
There are few machine learning algorithms out there to enhance the quality of fingerprint images. Further, I would like to investigate using deep learning and neural networks if I can create a model, which will be trained in fingerprint images with high quality and as an output, it should help images with lower quality to enhance the quality score without making any alterations related to minutiae in main image.
As this project was related to comparison, for further enhancement I would like to spend some time on fingerprint enhancement and recognition algorithms.

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I would like to show gratitude to the Ethics team of the University of Dundee as well, whose commitment to maintaining the integrity of this project was most important. Their diligent oversight made sure that the work related to this project was to the highest ethical standards, adding boundless credit to the outcomes.
A special mention must go to Phillippa Sterlini, the LLC senior research support officer, whose assistance was irreplaceable. Her support in getting access to necessary data was essential to this journey for which I'm immensely thankful.
My gratitude also extends to the Staff from the Computing Department to make sure we get access to the university laptop to work on this project to maintain security. Also, I'm thankful for the library IT support staff who helped us get the necessary software on the University machine.

Lastly, I would like to thank you, my family, and friends, who have shown constant moral support, patience and understanding. Their belief in my capabilities has been the true source of strength and motivation.

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Appendices

1. Jupyter notebook with code and instructions
2. Risk Assessment form
3. Ethics application and approval
4. Report
5. Poster
6. Time in minutes of meetings with the supervisor