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DETECTOR OF SKIN DISEASES BY FINGERPRINT TECHNOLOGY

DETEKTOR KOŽNÍCH ONEMOCNĚNÍ U TECHNOLOGIE OTISKŮ PRSTŮ

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Abstract

This work discusses detection of skin diseases in damaged fingerprint images and describes the solution implemented using image processing techniques.

Abstrakt

Práce se zabývá problematikou detekce kožních onemocnění z poškozeného obrazu otisku prstu a implementace jejího řešení pomocí technik zpracování obrazu.

Keywords

Image processing, object detection, skin diseases, fingerprint recognition.

Klíčová slova

Zpracování obrazu, detekce objektů, kožní onemocnění, rozpoznání podle otisku prstu.

Reference

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Detector of Skin Diseases by Fingerprint Technology

Declaration

Hereby I declare that this bachelor's thesis was prepared as an original author's work under the supervision of Assoc. Prof. Martin Drahanský. All the relevant information sources, which were used during preparation of this thesis, are properly cited and included in the list of references.

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Štěpánka Barotová
May 8, 2017

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Contents

Chapter 1

Introduction

Human beings have always had a need for a secure world, and with the speed of technology development in the recent past years this topic is becoming more and more important. Technology affects almost every corner of our lives: work, home, family and leisure. Our society has become more mobile, more electronically connected and less place-dependent. Humans want to have their technological devices, data, bank and other accounts, companies, cars or other possessions secured. However, traditional representations of identity such as passwords or cards no longer offer such security. Passwords are easily breakable and can be forgotten; cards can be stolen or lost. Biometric technologies are based on recognition of biometric traits of individuals, such as face, speech or fingerprint recognition, and they represent the most promising way how to provide security and represent identity in our growing modern world. [19]

Fingerprint-based systems are the most widely used biometric technology. Although the individuality of fingerprints was well known already in the ancient times, it was not until 1880 when Henry Faulds published a work that introduced the possibility of using fingerprints for the purpose of human identification. [7] Since that time, fingerprint technology has been evolving and nowadays fingerprint recognition systems have been applied in a variety of areas. [19] They are used not only in forensics for crime purposes but also as an access method to facilities, computers, mobile phones or electronic banking; as a data protection method and for civil identification (passports, driver licenses, national IDs), not to mention applications in government, commercial financial sector, education or health care. [19] This technology has been well accepted by people and we use it on a daily basis.

However, there is a significant number of people who cannot use fingerprint systems as easily because their fingertip skin is affected by some kind of skin disease. As these systems count heavily on the structure of an individual's fingertip papillary line pattern that positively determines their identity, people suffering from skin diseases might be discriminated against as their papillary patterns may be impaired. It is very likely that fingerprint devices have not been designed to deal with damaged fingerprints, and therefore after scanning the fingerprint, they usually reject it.

In some cases the condition of the image obtained from the damaged fingerprint is not even good enough for further processing, but in others the damage is minor and the condition of the fingerprint image should not be an obstacle for papillary lines and minutiae extraction, and further matching. The challenge now is to recognize the presence of skin

diseases in fingerprint images, provide sufficient algorithms that will detect them and, if possible, eliminate their influence on the fingerprint recognition process.

This goal of this thesis is to contribute towards the development of approaches, methods and algorithms that would eliminate the negative influence skin diseases have on the fingerprint recognition process, by designing and implementing a detector of three particular skin diseases: *atopic eczema*, *acrodermatitis*, *psoriasis* and *verruca vulgaris*. The resulting application will serve as a tool for future research, development and algorithms enhancement.

Chapter 2 gives a brief introduction to fingerprint recognition, in chapter 3 different fingerprint sensing technologies are introduced and chapter 4 describes human skin structure. In chapter 5, description and analysis of a diseased fingerprint database is given, along with diseases characteristics and their influences on the fingerprint image. Chapter 6 and 7 talk about the design approaches and implementation methods and in chapter 8, results and experiments are summarized.

Throughout this work, two very similar terms are used: *papillary lines* and *ridges*. Both stand for the same thing but *papillary lines* is used more from the medical point of view (the physical structure of skin, the whole papillary line pattern), whereas *ridges* is used from the biometric and computational point of view, and also in order to distinguish higher *ridges* from *valleys* between them.

Chapter 2

Introduction to Fingerprint Recognition

Fingerprint recognition is a not as simple process as it might look. Starting from the acquisition of a fingerprint image, called a *sample*, there are a number of challenges along the way. Fingerprint recognition systems are never 100% precise and the quality of their results sometimes cannot be compared to the work of a forensic expert. However, they bring many advantages, such as invaluable speed of processing and ease of storage.

There are two types of biometric systems: a *verification* system or an *identification* system [19]. The purpose of the former is to authenticate a person's identity by comparing their sample to the one that was captured previously. The latter recognizes a person by going through the whole database to find a match.

Regardless of whether we want to verify or identify a person, or even capture and store a sample and data of a completely new person's identity, in all cases the samples taken are involved in a similar fingerprint recognition process. The main steps of the process are as follows: [5]

1. **Fingerprint acquisition**. For capturing the digital image of a person's papillary lines structure, there is a wide range of fingerprint sensors to choose from, plus a traditional off-line ink or clean fingerprinting method. [19] As the quality of the sample is very important for the fingerprint recognition, it is necessary to choose a high quality sensor. [5] Chapter 3 describes the particular fingerprint sensing technologies in detail.

2. **Fingerprint enhancement**. After a sample is acquired, pre-processing image-enhancing steps improve the papillary lines structure for the following image processing, classification and matching. However, the enhancement steps differ for every fingerprint sensor and the results depend both on the environment conditions in which the sample was captured and on possible skin damage, skin humidity or dryness, or even dirt present on the finger.

3. **Fingerprint classification**. Every fingerprint is assigned to one of fingerprint classes according to its external shape. For this purpose, so called *singular points*, loop and delta, are useful. [19] This step speeds up the identification process because after determining the class, the fingerprint does not have to be compared with an entire database of fingerprints but only with fingerprints in that particular class. However,

it is a demanding process, because due to the variability of the fingerprint patterns, it is often difficult to determine which class the fingerprint belongs to. [19] [5]

4. **Minutiae extraction**. *Minutiae* are significant points in the papillary line structure. The combination of their positions and types is unique for each person and therefore is used for representing their identity. There are over 150 types of minutiae [19] but all of them consist of two basic ones (See Figure 2.2): the *ridge ending* and *ridge bifurcation*. This step can be problematic in low-quality fingerprints, for example those affected by some kind of a skin disease. The whole process of minutiae extraction is displayed in Figure 2.1.

5. **Fingerprint matching**. In this step, sets of minutiae from two fingerprint images, the template and the input, are compared. The result is a number of corresponding pairs of minutiae. After the comparison it can be stated whether or not the two fingerprints belong to the same person. [19]

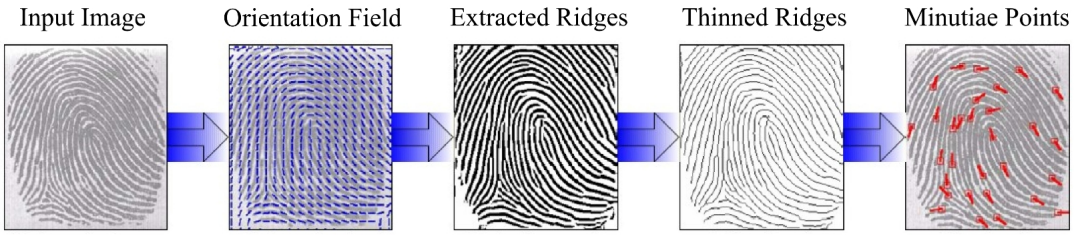

Figure 2.1: The minutiae extraction algorithm. Source: [5]

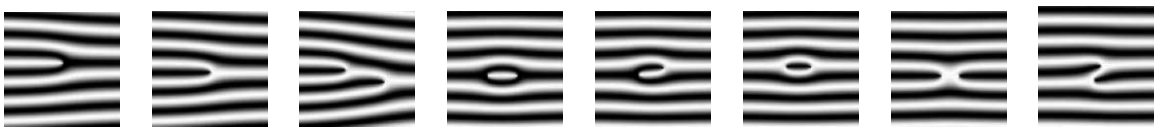

Figure 2.2: Minutiae types (from left: line ending, bifurcation, double bifurcation, interval, hook, whorl, crossing and bridge). Source: [5]

The topic of this thesis pertains partially to the second step of the fingerprint recognition process, i.e. fingerprint enhancement. Apart from that, none of the other steps are involved. In the future, it is hoped that some of the diseased fingerprint images are enhanced to the extent that the whole pipeline can perform better.

Chapter 3

Technologies for Fingerprint Sensing

In order to obtain the structure of a person's papillary lines in the form of a digital image, various sensing mechanisms can be used. In the past, samples were acquired using the so-called "ink-technique" during which fingertips were covered with black ink and pressed on a paper card. Another similar technique is "clean fingerprinting", which uses chemicals instead of ink. [19] These techniques are referred to as *off-line* fingerprint acquisition. Apart from that, there is a number of modern *live-scan* fingerprint readers that allow us to obtain a sample without the need to use ink.

Fingerprint scanners can be either single-finger or multi-finger. As the name suggests, only one finger can be scanned at a time using a single-finger scanner, whereas multi-finger scanners usually allow us to scan four fingers at once. The former are typically used in commercial and personal applications, while the latter in forensic or other large-scale applications. [19]

The general structure of a fingerprint scanner consists of a sensor that reads the ridge pattern of the finger and an A/D converter that converts the analog signal to the digital form. An interface module then communicates with external devices, such as a computer. [19] In this chapter, various types of sensing technologies are introduced and short descriptions of their functioning are provided.

3.1 Inked and Clean Fingerprinting

Historically, the inked fingerprinting method was naturally used first, as at the time of the initial development of the modern scientific fingerprint technique in the late nineteenth century [19], no electronic devices existed yet.

"Clean fingerprinting" is a similar method, in which a finger is soaked into a non-aggressive skin-sensitive chemical. After the chemical touches a special paper, a fingerprint papillary structure appears. The resulting fingerprints are usually rather high-quality.

In the past, fingerprints were recognized and compared manually and, after the acquisition, inked impressions of papillary structures were stored in dactyloscopic cards. Fortunately, these methods have been largely replaced by modern digital technologies.

3.2 Optical Technology

Optical sensors are based on a relatively simple principle. When the finger touches the protective glass surface of the top of the sensor, the left side of the finger is illuminated. And since the ridges touch the glass, while the valleys remain at a distance, the side illumination causes the ridges to be distinguished from the valleys and makes it possible for an integrated CMOS (Complementary Metal–Oxide–Semiconductor)or CCD (Charge-Coupled Device) camera to acquire the image of the fingerprint. [7] [19] [5]

3.3 Electro-Optical Technology

By touching an electro-optical sensor with a finger, two separate layers are connected and this connection causes fluorescent radiation. This radiation can be detected using an integrated camera that generates a digital fingerprint image. [7]

3.4 Capacitive Technology

A capacitive sensor constitutes of a matrix of small micro-capacitor conductive plates [19]. The density of the plates is higher than the density of papillary lines [7] and therefore when a finger touches the sensor, it acts as the other plate of each micro-capacitor and allows the creation of small electrical charges. The capacitance differences are used for the fingerprint image acquisition. [5]

3.5 Thermal Technology

Thermal sensors are based on the thermal radiation of human skin. Because ridges, being in contact with the sensor, have a higher temperature than valleys, which are at a distance from its surface [19], it is possible to acquire their image using a thermal sensor made of pyro-electric material. [5]

3.6 Pressure Sensitive Technology

Pressure sensitive sensors, also known as piezoelectric sensors [19], have a surface made of a non-conductive dielectric material (gel) which generates a small current when a finger is pressed on the sensor. The value of the current depends on the pressure, therefore pressures from ridges and valleys result in different amounts of current. [19] [5]

3.7 E-Field Technology

E-field sensors are able to acquire a high-quality fingerprint image from below the skin surface layer, which means less problems with wet or dry skin, or even diseases or other skin damage. [5] It is based on generating radio-frequency that creates an electric field from a ring around the sensing area. [5]

3.8 Ultrasonic Technology

Ultrasound sensing is based on sending acoustic signals to the fingertip surface and capturing the echo signal that bounces back. [19] This signal is afterwards used to compute the distance of ridges and valleys from the sensor. A great advantage of this technology is that it is able to capture the subsurface of the finger skin and therefore it is resilient to grease, dirt, etc. [5] [19] Although ultrasound sensors provide high-quality images, they are not yet widely used because of their high cost and large size. [5]

Chapter 4

Skin Structure

During the process of fingerprint recognition, since we work with the surface of human skin, it is important to be familiar with the basics of our skin structure.

Skin is an important body part with a number of functions essential to the proper functioning of our bodies. It serves as a communicator between the outside environment and the brain, it is able to feel touch, pain, pressure, hot and cold, it functions as a heat regulator, absorbs ultraviolet rays and protects us against them. Through skin, waste products are also eliminated and sweat is secreted onto its surface. [5] [12]

The skin is divided into three layers: *epidermis* (the outer layer), *dermis* and the *subcutaneous tissue* (fat layer) [12] [22].

4.1 Epidermis

Epidermis is the outer layer of skin and its primary function is therefore to form a barrier against the outside environment. It is constantly being regenerated. [22] [5]

4.2 Dermis

Dermis is a soft cushion of connective tissue directly below the epidermis. It is responsible for the skin's structural integrity, elasticity and resilience. In this layer, wrinkles are developed and also papillary lines are formed here. [5] It consists of collagen and elastic fibers [9]. It contains blood vessels and nerves, but no fat cells [9].

4.3 Subcutaneous Tissue

Subcutaneous tissue is a layer of fat cells below the dermis. It provides insulation and emergency energy supply. Its function is to protect the body from cold and trauma. [5] [22]

4.4 Influence of Skin Diseases on the Skin

There is a large number of skin diseases that affect the skin in some way. Generally speaking, these diseases can be classified into three groups: diseases causing histopathologic changes of the epidermis and dermis, diseases causing skin discoloration and diseases causing histopathologic changes in the junction of the epidermis and dermis.

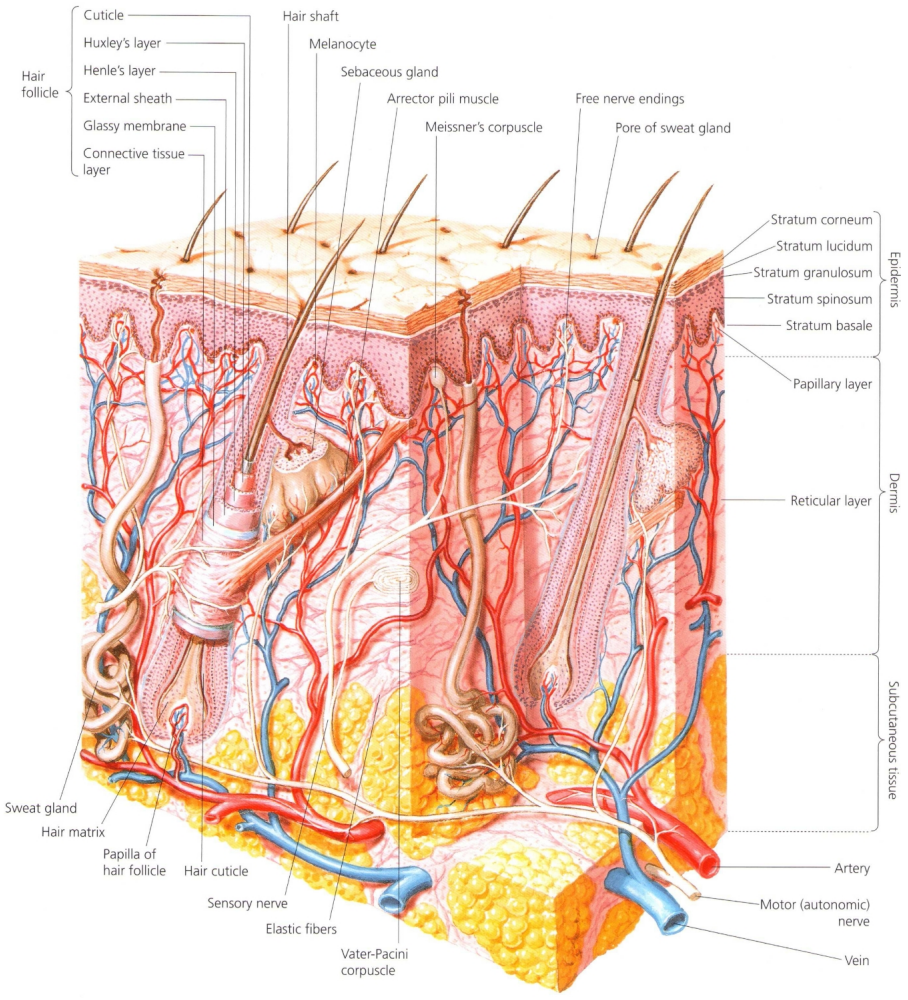

Figure 4.1: Skin structure. Source: [12]

Diseases from the first group cause problems to all types of fingerprint scanners because they affect both the color and the internal structure of the epidermis and dermis. [3] Once the papillary line structure has changed, it is difficult to recognize the original pattern and therefore often impossible to determine a person's identity. Among diseases in this group are for instance *hand eczema*, *dyshidrosis*, *systemic sclerosis* or *Raynaud's phenomenon*. [3]

Diseases that cause skin discoloration are problematic for optical scanners and also for those scanners that support liveness detection based on the color of human skin. It is the least problematic group. A typical representative is for example *hand, foot and mouth disease*.

Diseases causing histopathological changes in the junction between epidermis and dermis also belong to the first group. However, the diseases from the third group also cause problems to ultrasonic scanners, because the ultrasound waves can penetrate under the epidermis. Therefore, their fingerprint sensing process is only affected by skin diseases that attack dermis as well. [3] Typical representatives are for instance hand eczema, verruca vulgaris or psoriasis.

Chapter 5

Diseased Fingerprint Database

This thesis builds upon previous research that has been done at the Faculty of Information Technology, Brno University of Technology. In particular, the acquisition of a diseased fingerprint database, database analysis and primary research concerning possible methods for detecting damaged fingerprint areas. [3], [1], [6]

The acquired database contains over 2,000 fingerprint images from patients suffering from various kinds of skin diseases. In total, 12 particular skin diseases were obtained. [3] The database was thoroughly analyzed in order to find any common features in the damage caused by the diseases. Features that were found were classified into 5 categories that are later used for the disease detection itself. [1] In this chapter, a detailed description about the process of acquisition and analysis is given, as well as characteristics of each skin disease from the database and characteristics the specific influence they have on the resulting fingerprint images.

5.1 Database Acquisition

In cooperation with medical experts, a database of diseased fingerprint images was collected. For these reasons special dactyloscopic capturing stations have been designed. The stations were equipped with the following components: [3]

- laptop with a capturing application installed
- set of electronic dactyloscopic sensors
  - Sagem MSO 300 (optical sensor)
  - UPEK EikonTouch 500 (capacitative)
  - UPEK Eikon II Fingerprint Reader (capacitative)
  - TBS 3D Enroll Series 2011(optical multi-spectral)
  - digital microscope DinoLite Pro
- dactyloscopic card and special ink
- laboratory stand with boss and clamp for microscope

Using this capturing station, it was possible to collect 2,165 fingerprints from 44 patients who were affected by various kinds of skin diseases. [1]

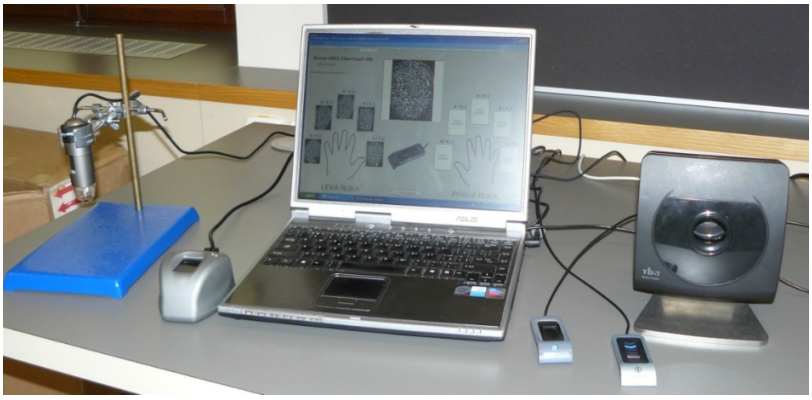

Figure 5.1: One of the capturing stations. Source: [3]

5.2 Database Analysis

The raw diseased fingerprint database was first analyzed in order to provide a solid foundation for future research. For every particular disease, common signs among all fingerprint images affected by this disease were found and a general description of each disease and its influences was defined. Based on these descriptions and sets of common signs and their frequencies, the diseased fingerprint images were classified into 5 categories. These categories are later used in the actual detection of the damaged areas in a fingerprint image and they help to divide the large detection task into smaller bearable parts. [1]

Most of the fingerprint images come from a dactyloscopic card. The numbers of fingerprints of each disease is displayed in table 5.1.

Table 5.1: Database content.

Disease	**No. of fingerprints in the DB**	**Percentages [%]**	**No. of patients**
Fingertip eczema	1,107	51.132	17
Psoriasis vulgaris	326	15.058	9
Dyshidrotic eczema	247	11.409	4
Hyperkeratotic eczema	118	5.450	2
Verruca vulgaris	96	4.434	4
Scleroderma	50	2.310	1
Acrodermatitis continua	40	1.848	1
Colagenosis	36	1.663	1
Raynaud's phenomenon	9	0.416	1
Effusion of fingers	35	1.617	1
Cut wound	18	0.831	2
"Unknown" disease	83	3.834	1
Total	**2,165**		**44**

By observing and comparing the fingerprint images, 12 common features were defined. 7 of them are local features:

- straight lines (SL),

- a grid (G),
- small papillary lines disruptions (PLD),
- small "cheetah" spots (CS),
- larger round/oblong spots (ROS),
- large irregular spots (IS) and
- dark places (DP).

The other 5 were global image patterns:

- blurriness of (parts of) the image (B),
- a significantly high contrast of the image (HC),
- the entire fingerprint area affected (EA),
- total deformation of the fingerprint image (TD) and
- a significantly high quality and healthy fingerprint (HQ).

For every disease its image features were counted (see tables 5.2 and 5.3). Fingerprint images obtained from optical scanners were excluded as their character is significantly dissimilar to the others. The actual number of images taken into account is stated in the column "sum".

Table 5.2: Local features of damaged fingerprint images.

	Percentages of particular features [%]							
Disease	**SL**	**G**	**PLD**	**CS**	**ROS**	**IS**	**DP**	**Sum**
Fingertip eczema	72.03	24.65	15.91	12.24	32.34	16.61	15.73	572
Psoriasis vulgaris	40.37	6.42	2.75	12.84	48.17	32.57	62.84	218
Dyshidrotic eczema	63.11	7.38	14.75	18.03	78.69	29.51	32.79	122
Hyperkeratotic eczema	3.92	0	66.67	15.69	74.51	3.92	5.88	51
Verruca vulgaris	3.17	0	14.29	12.7	74.6	0	25.4	63
Scleroderma	0	0	0	0	0	0	30.43	23
Acrodermatitis continua	14.29	0	0	85.71	60	14.29	65.71	35
Colagenosis	100	78.13	0	0	15.63	0	25	32
Raynaud's phenomenon	0	0	100	0	0	0	0	8
Effusion of fingers	10	0	73.33	43.33	63.33	6.67	13.33	30
Cut wound	93.75	0	0	0	18.75	0	12.5	16
"Unknown" disease	100	86.67	0	0	76.67	30	73.33	30

5.3 Characteristics of Present Diseases

This section gives an overview of all the diseases present in the database, their characteristics and description of their influence on resulting fingerprint images. [1] For detailed description of skin diseases mentioned in this thesis, please refer to [14], [24] and [12]. This thesis deals with the detection of four of them: *atopic eczema*, *acrodermatitis*, *psoriasis vulgaris* and *verruca vulgaris*.

Table 5.3: Global features of damaged fingerprint images.

	Percentages of particular features [%]					
Disease	**B**	**HC**	**EA**	**TD**	**HQ**	**Sum**
Fingertip eczema	18,01	21,5	40,38	36,36	29,02	572
Psoriasis vulgaris	34,86	27,06	61,93	58,72	18,35	218
Dyshidrotic eczema	30,33	30,33	31,97	29,51	9,84	122
Hyperkeratotic eczema	31,37	29,41	9,8	0	37,25	51
Verruca vulgaris	19,05	80,95	7,94	7,94	76,19	63
Scleroderma	0	0	0	0	100	23
Acrodermatitis continua	48,57	25,71	100	100	0	35
Colagenosis	9,38	40,63	0	0	25	32
Raynaud's phenomenon	0	0	0	0	100	8
Effusion of fingers	23,33	16,67	40	16,67	3,33	30
Cut wound	37,5	68,75	0	0	50	16
"Unknown" disease	30	20	90	83,33	0	30

5.3.1 Fingertip eczema

Fingertip eczema is a very dry, inflammatory, non-infectious disease which occurs on the palmar surface or the fingertips. The skin becomes cracked and scaly, and usually starts peeling off which results in exposition of red and tender skin surfaces. [14] [12] [24]

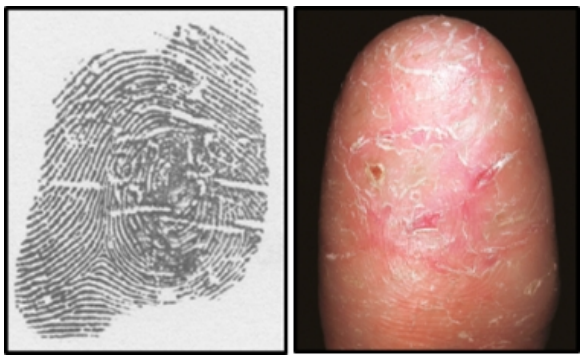

Figure 5.2: Fingertip eczema. Source: database and [12].

As the number of fingerprints with fingertip eczema in the database is large, a wide range of typical features was observed. There are two groups of these fingerprints: (i) less and (ii) more severely damaged. In the first group of fingerprints, occurrence of thin lines of different directions was typical. These lines often connect or cross each other. In some cases, small round white spots were present, and in others, occasional dark areas make the papillary lines partially unreadable. However, overall, papillary lines of fingerprints of the first group are generally very well readable and it is possible to remove the influence of the disease from the fingerprint.

In the second group, the damage is more severe. Fingerprints are usually almost completely damaged, straight lines cover the entire fingerprint area and create grids by crossing each other. The background is darker and large irregular spots can be seen. As the papillary lines cannot be seen at all, this type of damage is by no means recoverable.

5.3.2 Psoriasis vulgaris

Psoriasis is a common, chronic and inflammatory disease of the skin which is often indistinguishable from a serious form of hand eczema. It is characterized by dry and scaling plaques covered with dry scales that peel in layers. [14] [12]

The vast majority of fingerprints affected by psoriasis are completely damaged. Papillary lines are mostly unreadable. The most frequent feature is a large irregular dark spot bounded by a white border. Apart from this feature, the presence of larger dark areas or thick lines is also common, as well as round and oblong spots.

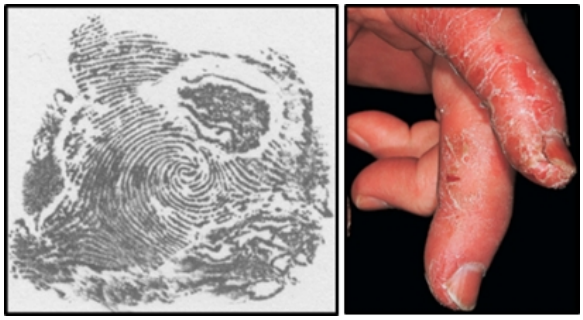

Figure 5.3: Psoriasis vulgaris. Source: database and [12].

5.3.3 Dyshidrotic eczema

Also known as pompholyx, this disease is a variant of hand and foot dermatitis that makes skin extremely dry. Its typical features are itching vesicles and scales located on the palms and sides of fingers. [12]

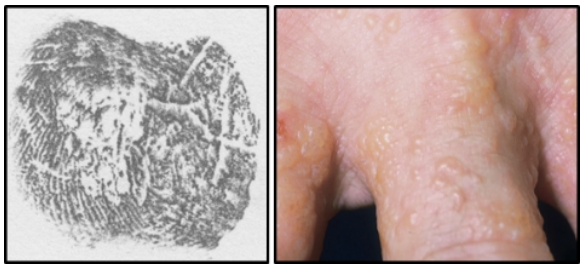

Figure 5.4: Dyshidrotic eczema. Source: database and [24].

Fingerprint images damaged by dyshidrotic eczema are generally covered with irregular blurred shapes with no specific form. Another typical feature is a thick line. These fingerprints were divided into two groups, according to how severe the damage is.

In the first group of less severely affected fingerprints, the entire area of a fingerprint is often covered, but papillary lines remain visible. Papillary lines are usually disrupted at multiple places and irregular blurred white spots may appear.

Fingerprints in the second group are seriously damaged and cannot be repaired. The image area is typically covered by thicker lines in combination with large blurred white spots. Papillary lines are not sufficiently visible.

5.3.4 Hyperkeratotic eczema

A chronic form of hand eczema characterized by the occurrence of orange and brown scales with cracks between them. [14] [12]

Only one third to one half of the fingerprint area is usually affected. Sometimes, only the papillary lines are multiply disrupted. In other cases however, papillary lines are distorted and their direction is difficult to determine. Small to medium round spots are likely to be present.

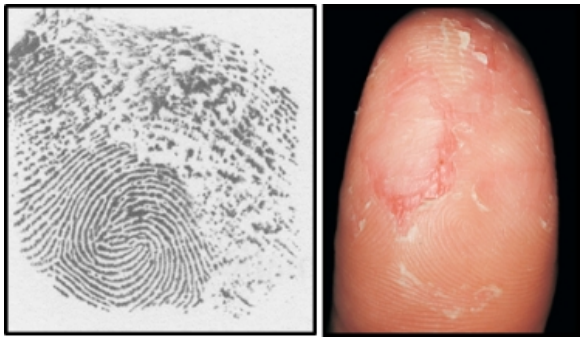

Figure 5.5: Hyperkeratotic eczema. Source: database and [12].

5.3.5 Verruca vulgaris (warts)

This is a very common skin disease, characterized by the presence of stiff elevated bumps on the skin surface. They grow in size which is in average about 5 mm but can reach up to more than 1 cm. On their surface, tiny black dots may appear. [14] [12] The influence of this disease on the fingerprint images is minor and easily removable.

Typically, 1 to 4 round white spots occur, sometimes with black dots in their center.

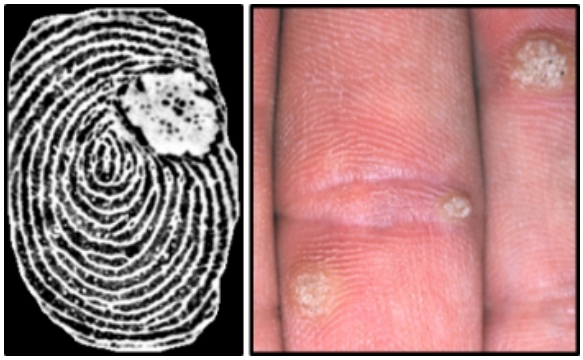

Figure 5.6: Verruca vulgaris. Source: database and [12].

5.3.6 Systemic scleroderma

Scleroderma is characterized by the appearance of hard, smooth and ivory-colored areas.

In the early stage, affected areas are red and swollen; later, they become completely immobile and lose their natural peaked contour. [14] [12] The fingerprints in the database

did not show any signs of damage. It can be therefore concluded that the number of acquired fingerprints was not sufficient to describe the disease's influence on fingerprint images.

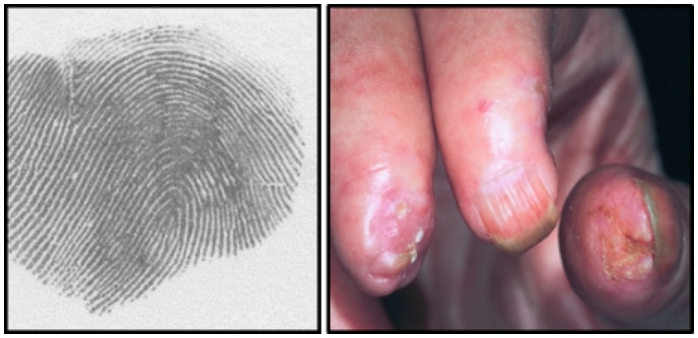

Figure 5.7: Systemic scleroderma. Source: database and [12].

5.3.7 Acrodermatitis continua

Also known as acrodermatitis continua of Hallopeau or dermatitis repens, this disease is a chronic inflammatory disease of the hands and feet, and one of the less frequent types of psoriasis vulgaris. The outbreak of the disease is accompanied by asymmetric formation of pustules of the fingertips, and continues with eruption of fresh pustules with hyperkeratotis and crusting. As the disease progresses, nails can even float away. [14]

Fingerprint images are typical for the occurrence of small round spots that look like a cheetah skin and cover usually the whole fingerprint area. Larger oblong or round spots occur as well and straight lines or cracks are also not uncommon. Papillary lines cannot be recognized at all, and the original structure of the fingerprint is completely covered. Larger dark areas are often present and the spots can be blurred together. Almost in all cases, the fingerprint image is completely damaged and cannot be repaired.

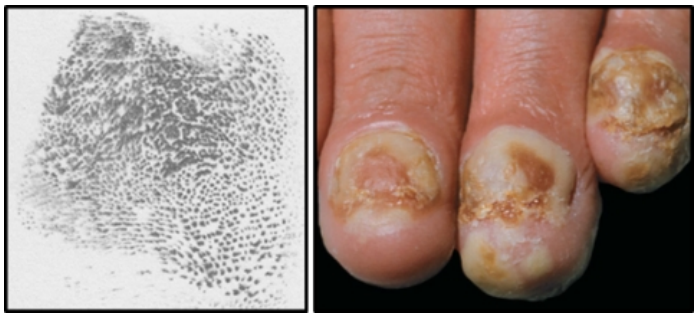

Figure 5.8: Acrodermatitis continua. Source: database and [24].

5.3.8 Colagenosis

Colagenosis is a connective tissue and inflammatory autoimmune disease. [11] The only typical feature of fingerprints with this disease is thin lines crossing each other. Under these lines, papillary lines are well visible.

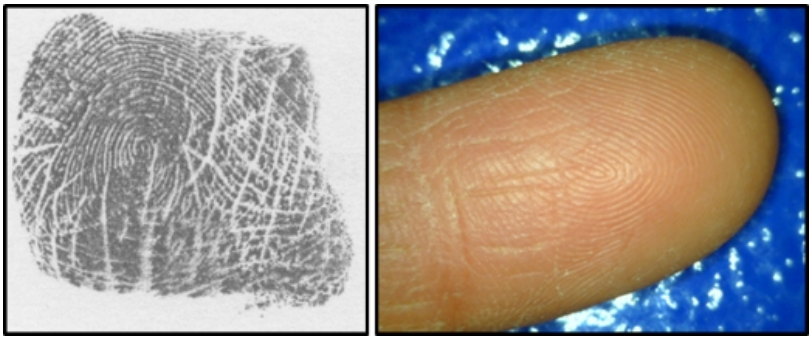

Figure 5.9: Colagenosis. Source: database.

5.3.9 Raynaud's phenomenon

A vascular skin disease that often accompanies an associated disease (most often scleroderma). The fingers have sequential discolorations: they first become pale and cold, then white, blue and finally red. This is caused by constrictions of the small arteries and arterioles in fingers. [14] [12]

As Raynaud's phenomenon causes discoloration only, fingerprints in the database are always healthy and undamaged.

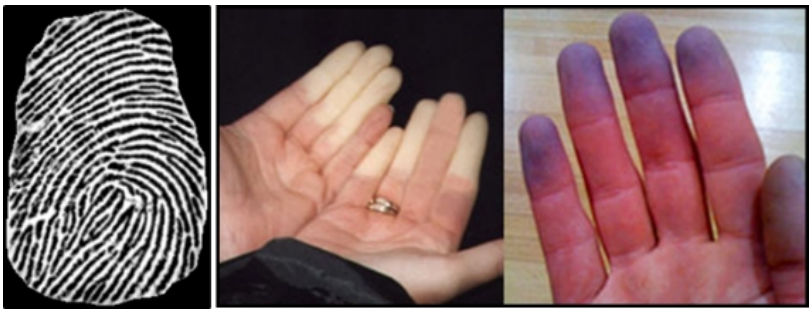

Figure 5.10: Raynaud's phenomenon. Source: database and [15].

5.3.10 Effusion of fingers

Although being stated as a disease in the database, effusion of fingers is only a syndrome which manifests itself by a strong swelling. It is one of the symptoms of systemic scleroderma, for instance.

Papillary lines are typically disrupted in many places, and small to medium spots are present. In general, papillary lines are clearly visible. Sometimes, however, white spots make them unreadable.

5.3.11 Cut wounds

A cut wound typically cause either a straight line in a fingerprint image or a more blurred white area. The damage is minor and should not be difficult to remove.

5.3.12 "Unknown" disease

Fingerprints of this unnamed disease are totally covered with lines of different thickness and length and are therefore unreadable. They are very much alike those with fingertip eczema.

Figure 5.11: Effusion of fingers, cut wound and "unknown" disease. Source: database.

5.4 Classification of Damaged Fingerprint Images

Based on the analysis of the database, the diseased fingerprint images were classified into 5 basic feature classes. Such classification is supposed to help access each type of damage individually and facilitate the detection process. For each disease detector a different combination of features to detect is chosen, which helps differentiating between signs of particular diseases and correctly determining the type of disease present in the fingerprint image.

Straight lines and grids
Fingertip eczema, cut wound, colagenosis, dyshidrotic eczema, "unknown" disease.

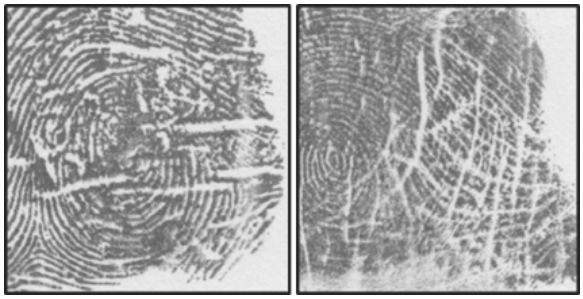

Figure 5.12: Example of fingerprint images with straight lines or grids. Source: database.

Small papillary lines disruptions
In this case, papillary lines are disrupted at multiple places but no significant damage is present. Representatives are: dyshidrotic eczema, hyperkeratotic eczema, effusion of fingers and fingertip eczema.

Small "cheetah" spots
The only representative of this group is acrodermatitis.

Figure 5.13: Examples of papillary lines disruptions and "cheetah" spots. Source: database.

Round/Oblong spots
Although round or oblong spots occur in most diseases, typical representatives with a significant amount of them are: verruca vulgaris, effusion of fingers, and psoriasis.

Figure 5.14: Example of fingerprint images with white spots. Source: database.

Large irregular spots
Psoriasis and severe form of fingertip eczema often cause extreme damage to the fingerprint and one of their features are also large spots of irregular shapes.

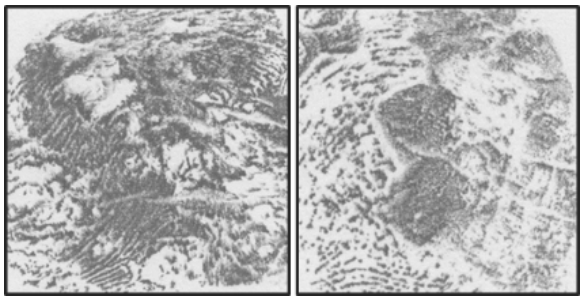

Figure 5.15: Example of fingerprint images with irregular spots. Source: database.

Also, diseases were classified into 3 categories according to the seriousness of the damage:

1. **Minor damage**: verruca vulgaris, Raynaud's phenomenon, cut wound, scleroderma.
2. **Medium damage**: mild form of fingertip eczema, mild form of dyshidrotic eczema, hyperkeratotic eczema, effusion of fingers, colagenosis.
3. **Major damage (unrecoverable)**: acrodermatitis, severe form of fingertip eczema, severe form of dyshidrotic eczema, psoriasis, "unknown" disease.

Chapter 6

Application Design

Based on the database analysis, an application capable of detecting four types of skin diseases from fingerprint samples was designed and implemented. The program consists of two main parts, a *Detector* and a *Classifier*, and provides a graphical user interface (GUI). In this chapter, the description of the application design is covered and explained in more detail.

6.1 Application Goals

Because the main objective of this work is to develop a detector of skin diseases, the resulting application's primary function is the ability to classify an image according to the specific features found during the detection process. The program outputs a suggestion of a disease that most likely matches the characteristics of the input image and which therefore could be the disease the patient might possibly suffer from.

Apart from the obvious main emphasis of the program, the application possesses other sub-goals that logically follow the major one:

1. To extract all damaged areas from the fingerprint sample.
2. To distinguish between healthy, partially damaged and unrecoverable fingerprints.
3. To visualize the whole detection process.

The goals were achieved by designing and implementing a GUI application, whose two main building blocks are going to be discussed in the following section.

6.2 Application Design Overview

As mentioned above, the application consists of the Detector and the Classifier. Both of them use many smaller supporting parts of the program, for instance algorithms for image preprocessing and normalizing the fingerprint sample.

The task of the Detector is to extract the damaged image areas, to record their properties, such as size, shape and location, and assign their type, if possible. Along with the detection process, the Detector calculates an estimated overall extent of damage in a fingerprint image (in percentages) and provides graphical feedback by visualizing the global

distribution of damage in the sample using a color scale.

The classification process of the Classifier itself is dependent on the number and types of disease features provided by the Detector. The decision is made based on a set of rules that resulted from the database analysis and the final result is shown to the user in the GUI.

6.2.1 Detector Design

Since there is a wide range of possible types of damage that could occur in a fingerprint image, the Detector consists of a number of sub-detectors, each for a different type of damage.

- White Spots Detector
- Lines Detector
- "Cheetah" Spots Detector
- Papillary Lines Disruptions Detector
- Orientation Field Discontinuity Detector
- Histogram Detector

Each of them includes a preprocessing part and a features extraction part. The extraction is based on three distinct methods: Flood Fill (for the first four detectors), Block Orientation Field and Histogram Analysis. The specific behavior of the methods is explained in Chapter 7 (Implementation).

The Detector outputs a list of extracted features and their properties, which are later used in the classification process.

6.2.2 Classifier Design

The Classifier is a single class which implements the decision rules. It requires a vector of features extracted by the Detector and outputs the resulting disease.

The whole application design is graphically displayed in Figure 6.1.

6.3 Classes

The class design is based on the MVC (Model-View-Controller) design pattern [8], as it is a program with frontend and backend parts. The Model is represented by detectors (`BlackSpotDetector`, `WhiteSpotDetector`, `OrientationsDetector` and `Histogram-Detector`) and the `Classifier` class, the View is represented by `MainWindow`, and the class `PipelineMaster` stands for the Controller.

Since the detectors share the same design, they all inherit from an abstract class `AbstractDetector`. In this manner, it is ensured that the detectors will have the same interface.

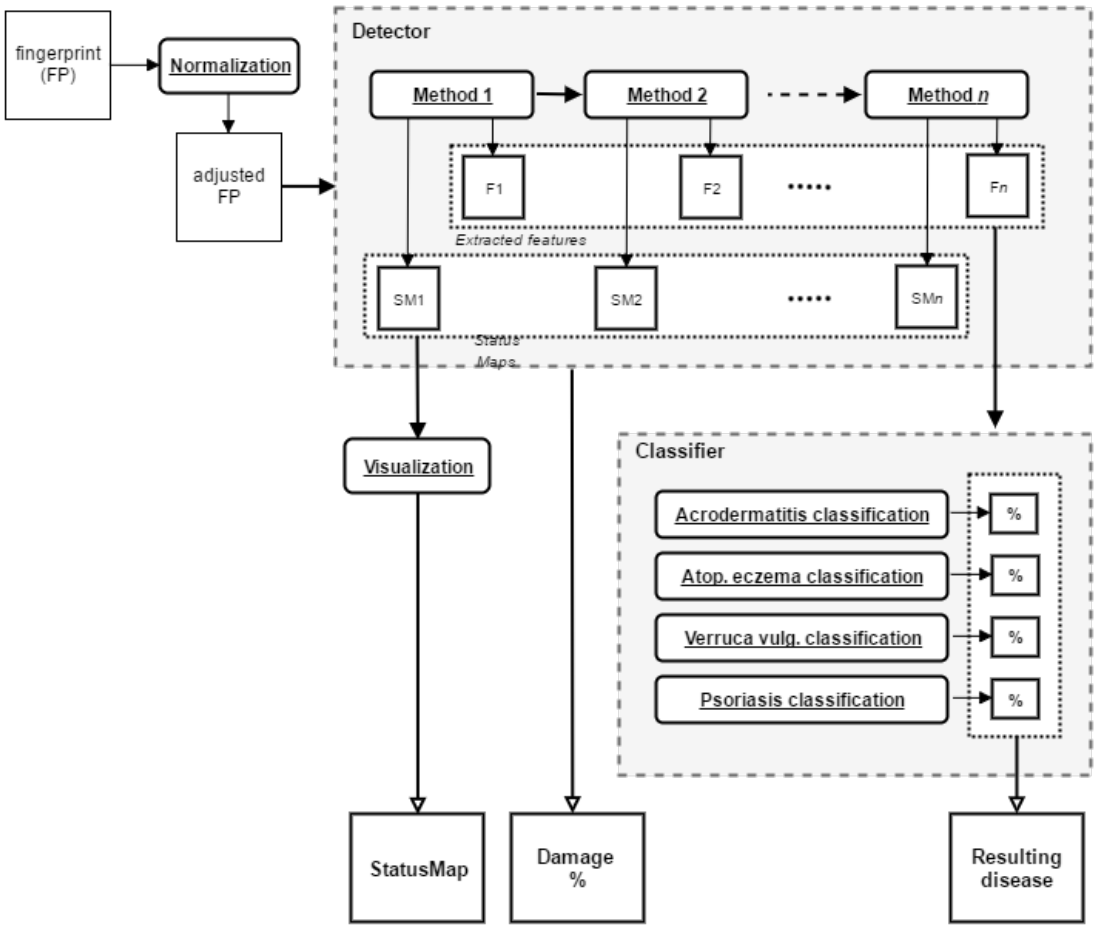

Figure 6.1: Application high-level design. Fx stands for sets of extracted features from each method and SMx stands for `StatusMap`, a data structure holding the information about the extent of damage in the image that serves for visualizing purposes.

`PipelineMaster` takes care of managing the whole detection and classification process, transmitting the input parameters from the GUI and retrieving the results.

There is a number of important supporting classes. To mention the most significant ones, `FloodFill` encapsulates the algorithm of the same name, `Histogram` provides methods for histogram analysis, `BckgrExtractor` separates the fingerprint area from the background, as the name suggests, and `StatusMapper` ensures a correct connection of the detection results together. There are also classes created for the purpose of storing and keeping data only: `StatusMap`, `DamagedArea`, `Peak` and `Step`. `BasicOperations` groups elementary image processing algorithms and `Normalizer` contains algorithms for the normalization of a fingerprint. An overview of a simplified class design is given in Figure 6.2.

6.3.1 Data Flow

From the design point of view, it is important to determine the inputs and outputs of particular classes and describe the data flow in the application.

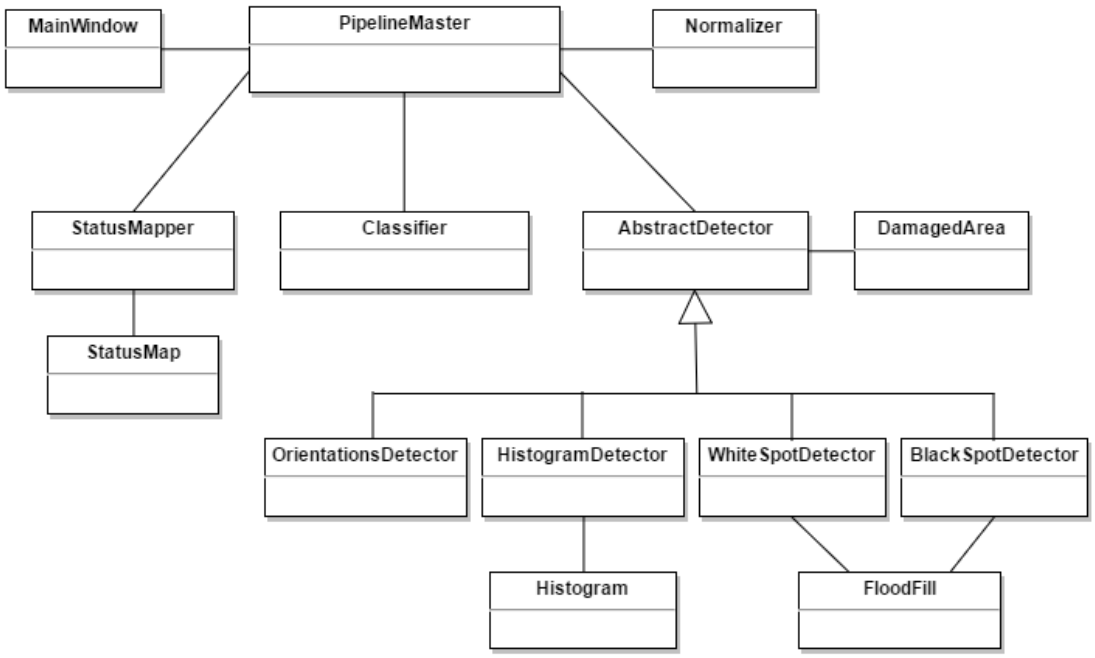

Figure 6.2: Simplified application class design.

A fingerprint image is the input given by the user through the GUI. `PipelineMaster` takes this image and passes it into the main pipeline and in the end it retrieves the following outputs: a suggested disease, an estimated percentage of the overall extent of damage, a vector of extracted features and their attributes, the visualization of the overall damage in the form of a `StatusMap`, and a vector of intermediate steps to be shown to the user.

The detectors require a normalized fingerprint image as an input, and they output a vector of detected features, a vector of intermediate steps and a `StatusMap`, which keeps the information about the extent of damage of each pixel.

The joined extracted features go into the `Classifier` whose output is the suggested disease.

6.4 Graphical User Interface and Application Usage

The application was designed with a graphical interface that allows the user to load a fingerprint image or a whole folder of images that he can easily scan back and forth using buttons. The GUI displays a number of tabs, the first of them contains some settings so that the detection process could be adjusted. The "Run" button starts the process and before it displays the final results in the "Final" tab, such as the percentage of damage, the suggested disease and visualized disease features, it also shows the process' intermediate steps, including preprocessing and all the methods.

The GUI also enables the user to save the results to his personal computer.

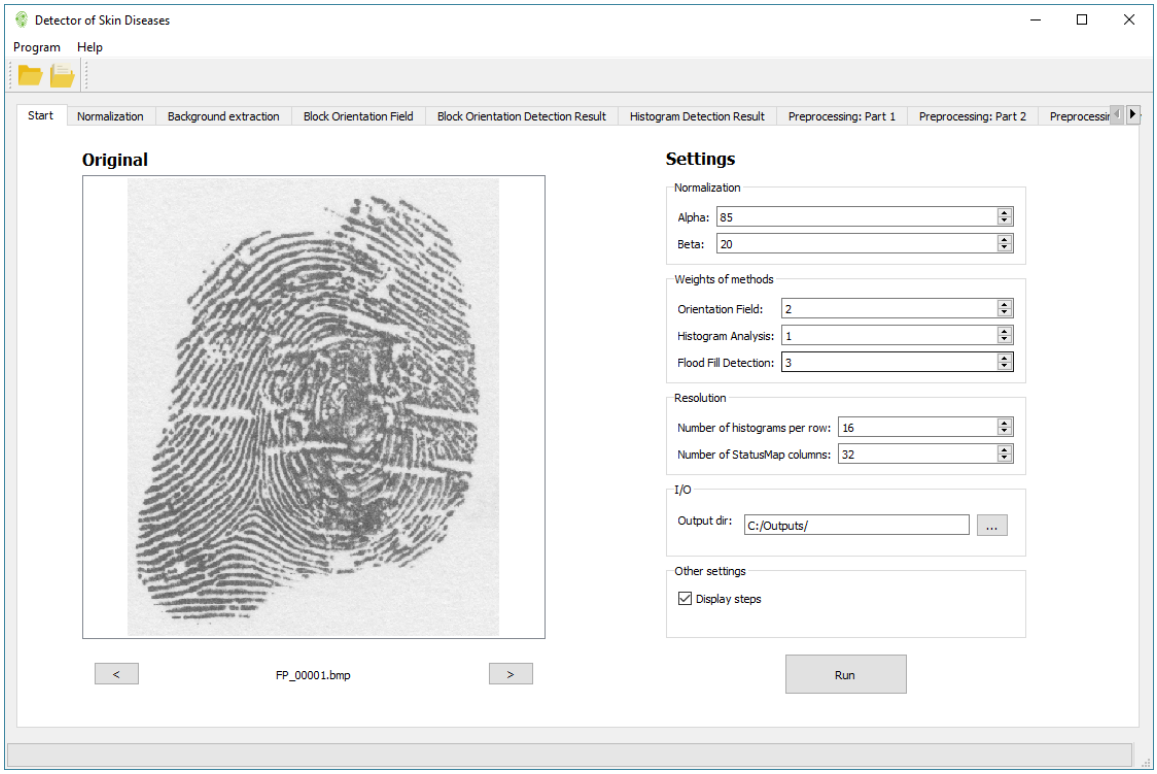

Figure 6.3: Screenshot of the application.

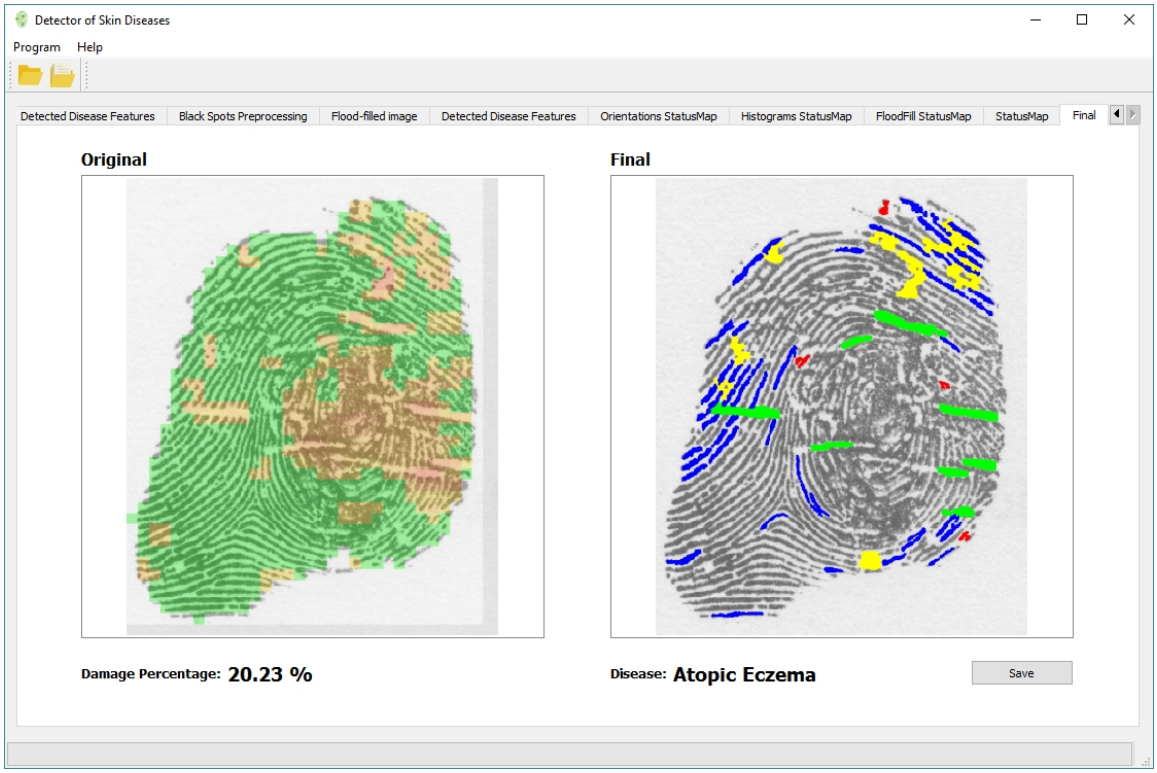

Figure 6.4: Screenshot of the application.

Chapter 7

Implementation

The application was developed in C++ and Qt 3.5.1 (open source), using the Computer Vision library OpenCV, version 2.4.11 (BSD licence).

In this chapter, the specific algorithms used in the disease detector along with their advantages and shortcomings will be discussed, as well as the core methods essential for the program's functionality and data structures used to store and keep important data throughout the process.

7.1 Detector

There are three major algorithms that are used for the detection part: Block Orientation Field, Histogram Analysis and Flood Fill. Their combination provides valuable information about the fingerprint quality and character of the possible disease.

The Detector uses a few special data structures. The first of them is `cv::Mat`, a data type implemented in OpenCV used for storing images [10], in other words a matrix of numerical values. The program makes use of this data type not only for keeping the processed images themselves, but also for storing the intermediate steps and `StatusMaps`.

A `StatusMap` is a data structure that is used for the visualization of the extent of damage in the fingerprint. It consists of an $n \times m$ matrix (`cv::Mat`), where n is the number of columns and m is the number of rows. Both n and m are always smaller than the width and height of the input image so that the visualization can capture the global extent of damage in $w \times w$ subfields of the image. The values of this matrix are between -1 and 1. Negative values stand for background, 0 stands for a healthy area and positive values imply a damaged area, with 1 being the most damaged.

$$x = \begin{cases} (-1; 0) & \text{if if the subfield belongs to background,} \\ 0 & \text{if the subfield belongs to a healthy area} \\ (0; 1) & \text{if the subfield is damaged} \end{cases} \tag{7.1}$$

Another essential data structure is the Feature. It is used to store the signs of diseases extracted from the image and consists of a feature type, location of the first pixel, size and the exact pixels belonging to that particular area. It is used both for storing the detection results and visualizing them.

7.1.1 Block Orientation Field

The computation of block orientation field is commonly used in the fingerprint recognition process for the purposes of estimating the ridges direction and classifying the fingerprint image into one of the several fingerprint classes [19] [13] [4]. Because a typical fingerprint pattern consists of alternating dark and white lines, this information can be easily processed by a gradient operator that estimates the image gradient for each pixel. This low-level information is gathered and averaged for each $w \times w$ block in the image [17]. The transformation can result in a relatively smooth and continual image of the ridges direction estimates – for a healthy fingerprint of course - see Figure 7.1 on the left.

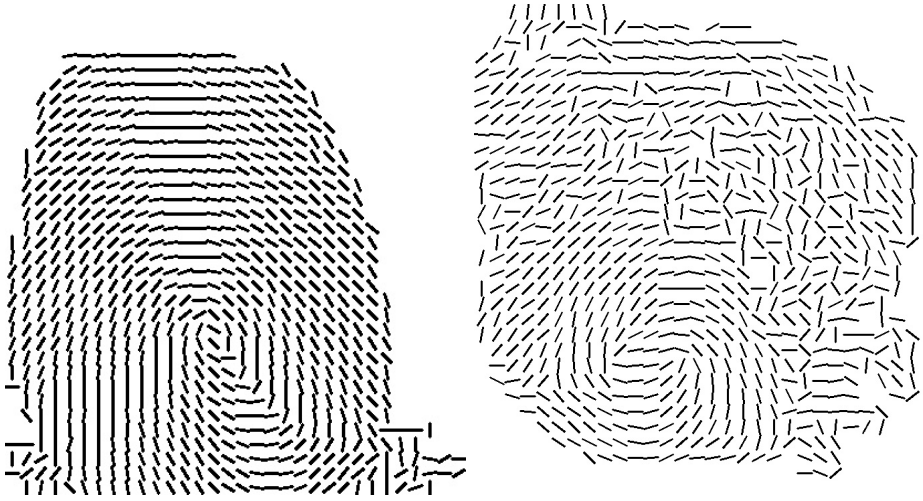

Figure 7.1: Examples of block orientation images (left: healthy fingerprint, right: fingerprint affected by a skin disease).

If we try to compute the block orientation field for a damaged or a partially damaged fingerprint however, we can easily recognize with the naked eye which areas contain possible damage, because the orientation field in these areas will be discontinuous, as displayed in Figure 7.1 on the right. Exceptions to this are the peripheral areas and deltas and cores. These discontinuities can be detected by scanning the field for differences in direction angles.

In the program's pipeline, a gradient-based method of block orientation field computation is used [17] [23]. Its steps are as follows [17]:

1. Compute the gradients ∂_x and ∂_y for each pixel at (i, j) using a gradient operator. In this case a simple Sobel operator was used.

2. Divide the original image into $w \times w$ blocks.

3. Compute the estimation $\theta(i, j)$ of the ridge orientation for every image block centered at (i, j) using the Equations 7.2, 7.3 and 7.4:

$$v_x = \sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{v=j+\frac{w}{2}} 2\partial_x(u, v)\partial_y(u, v) \tag{7.2}$$

$$v_y = \sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{v=j+\frac{w}{2}} \partial_x^2(u,v)\partial_y^2(u,v) \tag{7.3}$$

$$\theta(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{v_y(i,j)}{v_x(i,j)}\right) \tag{7.4}$$

The resulting block orientation field is afterwards analyzed for any discontinuities that may occur. The analysis is done using a row-wise and column-wise scanning approach that reveals areas of possible damage in the fingerprint. Neighboring blocks' directions are compared and a block is marked as a discontinuity if $|\theta(i,j) - \theta(i,j+1)| > 45\,^\circ$, where both estimations $\theta(i,j)$ and $\theta(i,j+1)$ have a value between $0\,^\circ$ and $180\,^\circ$

Sometimes, the method detects single discontinuities that may be erroneous, and on the other hand, under different circumstances, one unmarked block may appear in the midst of discontinuous blocks. In order to make the algorithm as accurate as possible, although mistakes never disappear completely, these cases are taken into account. The algorithm handles them by copying the properties of their neighboring blocks (marking the single ones either as alright or as a discontinuity, depending on the neighborhood). Example detection is shown in Figure 7.2.

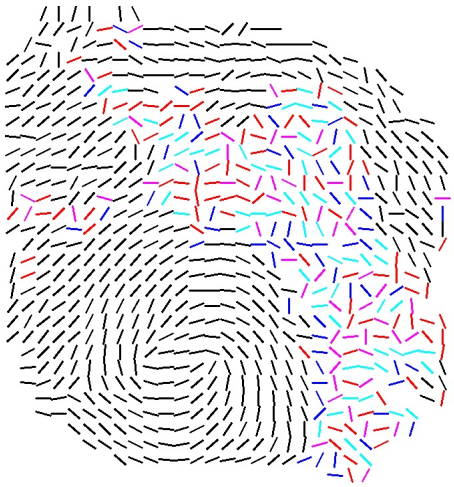

Figure 7.2: Damaged area detected using the orientation field.

The advantage of this method is that it is already a part of the standard fingerprint recognition pipeline, so the algorithm can be easily implemented into existing methods. Also, it provides a fairly accurate estimate of the fingerprint damage in the sample. However, it is not always able to detect local damages, such as spots or lines. For this reason we use the Flood Fill algorithm. Before that one is explained, however, let's take a look at how analyzing histograms from image subfields can be used to obtain useful information about damage.

7.1.2 Histogram Analysis

This method is based on the presumption that a quality fingerprint image consists of equally distributed ridges and valleys. If we assume that ridges are roughly the same dark color while valleys are light-colored, a histogram computed from each subfield of the fingerprint's area should ideally consist of two peaks of approximately the same height and one valley between them. The transition between the peaks and the valley should be smooth, as displayed in Figure 7.3, and the peaks' height difference vary slightly according to the width of ridges in the image. This shape is called *bimodal*.

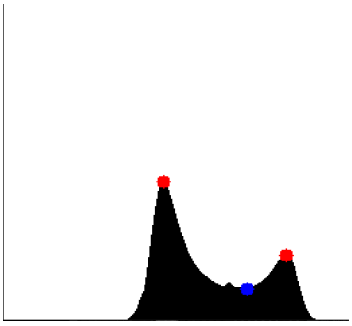

Figure 7.3: An ideal bimodal histogram.

On the other hand, the intensity distribution in a fingerprint image part that belongs to a damaged area is not always as equal as in the quality one. Thus, if a histogram is computed for this subfield, it is very likely that it will not have the ideal bimodal appearance as described above. Experiments showed that the majority of damaged areas break the rules of the bimodal histogram. The lower the quality, the less the histogram resembles the ideal one. A non-bimodal histogram always implies a damaged or low-quality area.

At the same time, however, there is a certain percentage of damaged areas whose histograms still fall into the valid category. A damaged subfield therefore does not necessarily imply a non-bimodal histogram. This is due to the fact that a histogram is a measure for the distribution of intensities only and it does not take into account the pattern or neighborhoods of pixels. Figure 7.4 shows examples of invalid histograms.

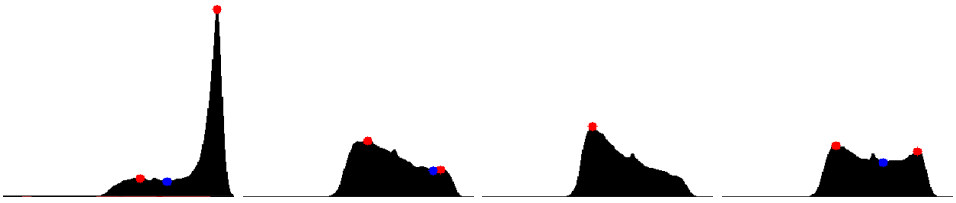

Figure 7.4: Examples of invalid histograms.

The steps of the algorithm are as follows:

1. Divide the image into $w \times w$ blocks (ROIs = regions of interest), according to the desired resolution.

2. For each ROI, compute a histogram.

3. Check if the histogram is valid.

   (a) Find all peaks and valleys of the histogram.

   (b) If $peaks == 2$ and $valleys == 1$, histogram is valid, so continue with 3c. Otherwise quit because the histogram is invalid.

   (c) Check the heights and distances of the peaks and valleys. If the histogram passes the validity tests, it is valid, otherwise it is invalid.

The following tests have been implemented. The decision parameters have been chosen based on experiments and testing. π stands for the number of pixels in the ROI.

- Peak height test: The dark peak must be between 0.003ρ and 0.025ρ, and the bright peak must be between 0.004ρ and 0.042ρ.
- Valley height test: The valley has to be lower than 0.0065ρ.
- The difference between peak heights: It has to be between 0.004ρ and 0.25ρ.
- The height difference of the valley and the lower peak: It must be greater than 0.0017ρ.
- The distance of the valley from the lower peak: It must be larger than 0.002ρ.

Figure 7.5 shows an example output of this method, along with the particular histograms that were being analyzed. Red background implies an invalid histogram, green means valid and blue stands for background.

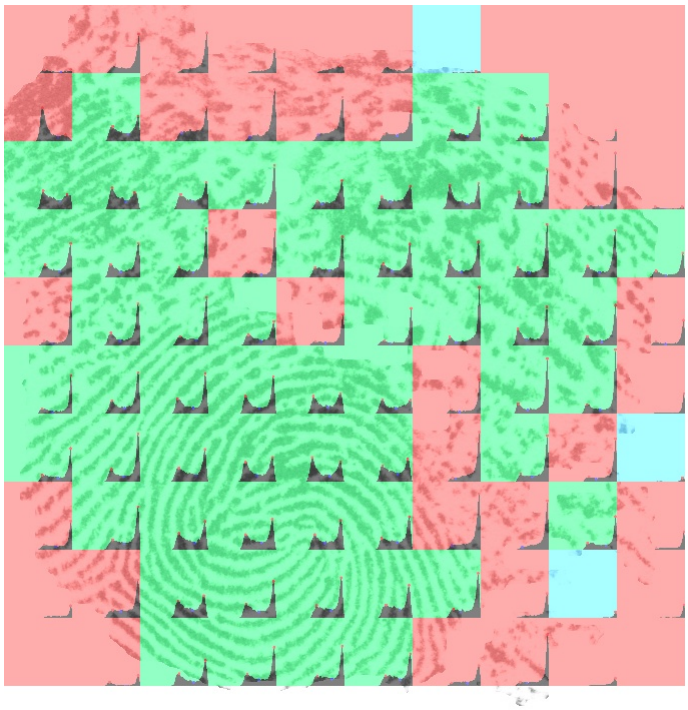

Figure 7.5: Histogram Analysis result with particular histograms.

Since the Histogram Analysis method is an experimental one, its results are not always accurate. The major drawback of this method is its inability to cope with low-quality, especially dark, images. By implementing appropriate preprocessing steps, the method's performance and accuracy can be improved.

Although the method can never find all damaged areas, Histogram Analysis is able to detect many areas the Block Orientation Field method might have omitted. The sets of damaged areas detected from these two methods are never identical, therefore the Histogram Analysis method is extremely valuable for the final determination of healthy areas.

7.1.3 Flood Fill

Flood Fill is a very well known algorithm used for graphical purposes [2] and is especially handy for detecting and filling connected single-colored areas of an image. This characteristics was used in the application in order to find local features of damaged fingerprints, such as straight lines or spots.

For the detection of such features, the Hough transform [10] was initially used, but it was later rejected for its inaccuracy. Flood Fill turned out to be far more exact and appropriate.

The Flood Fill algorithm has three parameters: a target color, a replacement color and a start pixel. It is based on examining the color of all pixels in the 4- or 8-neighborhood of the start pixel and changing the color of those pixels that have the target color to the replacement color. Using of either recursion, or stack/queue, the colored pixels become the next start pixels and the process is repeated. In the end, the entire single-colored area is filled.

The basic recursive FloodFill method steps are explained below:

if *targetColor == replacementColor* **then**
  return;
end
if *startPixel has a different color than replacementColor* **then**
  return;
end
Call FloodFill on the pixel above the *startPixel*;
Call FloodFill on the pixel below the *startPixel*;
Call FloodFill on the pixel on the right of the *startPixel*;
Call FloodFill on the pixel on the left of the *startPixel*;

In our case, for better memory management, the Scanline Flood Fill algorithm [2] is used. This one is extended by a stack and differs from its basic version by a reduced space and time complexity, which is achieved by filling whole lines instead of single pixels. Also, it is able to retrieve all points belonging to the area and store them later in the `Feature` class.

When Flood Fill is used for a fingerprint image, the sample first needs to be preprocessed in order to obtain a black and white image that can be used as an input for the algorithm. The preprocessing steps are tricky because they heavily depend on the image quality, as well as the type of sensor used for the acquisition. In this implementation, all algorithms

are tailored for our internal fingerprint database, in particular for the fingerprints from dactyloscopic cards.

The preprocessing steps consist of contrast and brightness adjustment, a series of dilations, erosions, closing and opening operators, combined with fingerprint area detection according to [18], Gaussian blur and thresholding [21] [16].

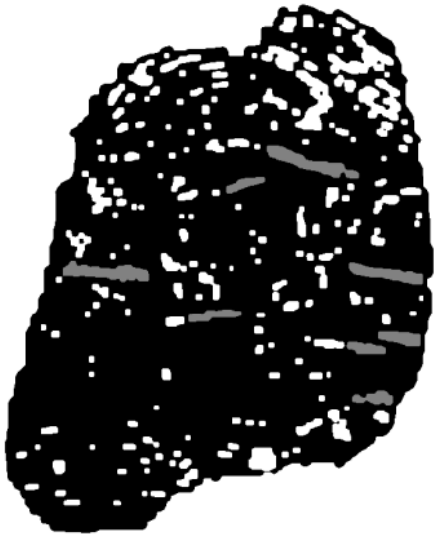

Figure 7.6: Extraction of straight white lines.

There are four types of features the Flood Fill algorithm is programmed to detect: large white spots, thick white lines, small "cheetah" spots and papillary lines disruptions (for explanation of the groups, see section 5.4).

Aside from the algorithm, the `FloodFill` class also enables us to set parameters that closely specify how big the filled areas should be and what shape they should have. The shape's determination is based on the ratio between the longer and the shorter side of the area's bounding rectangle: if it is below 1.8, it is considered round, and if it is over 2.3, it is considered oblong. Others are not taken into account. Thanks to the parameters, it is possible to tailor the results for different detectors. Details are showed in Table 7.1.

Table 7.1: Flood Fill parameters.

Detector	**Target color**	**Min. size**	**Max. size**	**Shape**
White Spots	white	500	20,000	round
Lines D.	white	500	12,000	oblong
"Cheetah" Spots	black	100	400	round
Disruptions	black	200	600	oblong

7.1.4 Methods Merging Using a Status Map

All three of the above-described methods detect a different kind of damage in the image and only Flood Fill provides logically structured results that can be used in classification.

However, connecting the three methods together results in a surprisingly accurate description of the extent of damage in an entire area of a fingerprint image.

At the end of each detection process, every image pixel is assigned a value between -1 and 1. Negative values stand for background, 0 means a healthy area and positive values indicate damage. The higher the value, the more damaged the area to which the pixel belongs, as explained in section 7.1.

The challenge was to connect these three output matrices together into a so-called `StatusMap` which would give a good overview of the damage state every $w \times w$ block of pixels.

For the purpose of a correct merge, all method's output pixel values were limited to non-negative. The information about background is stored separately using `BackgroundExtractor`. This extraction method marks pixels -1 (background), or 1 (fingerprint area) and produces a fourth matrix of pixel values.

This is the description of the `StatusMap` merging process:

1. Choose the resolution of the resulting `StatusMap`.
2. Get the three output matrices and a background matrix.
3. For each matrix, compute a generalized block matrix (=`StatusMap`) that will store the average pixel values from $w \times w$ blocks: m_1, m_2, m_3 and $bckgr$.
4. Assign a weight to each method, according to the desired output: w_1, w_2, w_3. It is possible to choose the weights in the GUI. Default values are: Orientation Field 2, Histogram Analysis 1 and Flood Fill 3.
5. For each block, compute its damage index. Damage index is a weighted mean of m_1, m_2 and m_3, masked by the value of the $bckgr$ matrix.

$$damageIndex(i,j) = bckgr(i,j) * \frac{w_1 * m_1(i,j) + w_2 * m_2(i,j) + w_3 * m_3(i,j)}{w_1 + w_2 + w_3}$$

6. $damageIndex$ now represents the extent of damage in each image block. Negative values are background, zero means a healthy area and positive values indicate damage, as described above.

The resulting `StatusMap` gives a very good overview of the damage.

7.1.5 Damage Percentage

From the final `StatusMap` values, a damage percentage can be calculated. The computation also takes into account the different damage indexes. The percentage is shown to the user in the GUI.

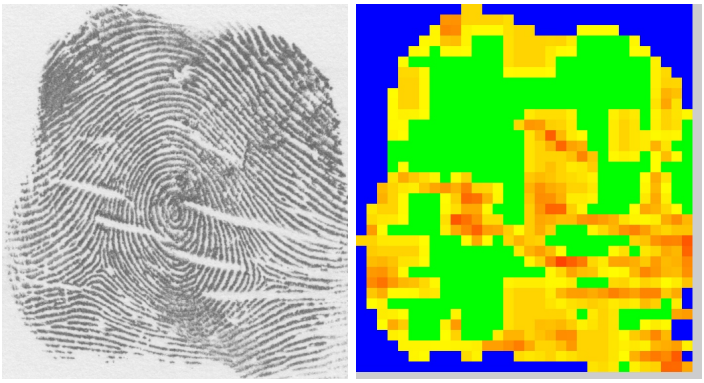

Figure 7.7: Example of a final `StatusMap`.

7.2 Classifier

The Classifier decides based on features extracted by the Flood Fill algorithm and classifies the fingerprint image, according to the features' numbers, sizes and shapes into one of these 6 categories: Acrodermatitis, Atopic Eczema, Psoriasis, Verruca Vulgaris, Unknown disease or Healthy.

In order to determine the decision rules, a script that counted the numbers and types of detected features from the whole database for each disease was implemented. Medians and standard deviations of these numerical values were used to support the Classifier's decision - see Table 7.2.

Table 7.2: Statistics of features extracted from each disease.

	Acrodermatitis		Atopic eczema		Psoriasis		Verruca vulgaris	
	med.	**std.dev.**	**med.**	**std.dev.**	**med.**	**std.dev.**	**med.**	**std.dev.**
white sp.	5	3.97	5	4.31	8	5.35	1	3.02
lines	2	1.84	3	3.06	4	2.65	1	1.63
cheetah sp.	47	42.70	29	17.50	21	19.61	18	10.90
disruptions	7	8.37	17	19.80	8	9.22	15	39.76

Given the normal probability distribution, it is supposed that the majority of values are going to be one standard deviation away from median. Then, a significant amount of values will lay two standard deviations away from median and almost no values will be farther. These characteristics are used in order to compute an estimated likelihood that a certain set of features belong to a particular disease.

The classification algorithm steps are as follows:

1. For each disease do:

   (a) For each extracted feature type, compute its likelihood that it could belong to a particular disease class. *dist* means the distance of a certain feature's number from the median and exact value in the third case is computed using direct proportion.

$$likelihood = \begin{cases} 0.9 & \text{if } dist < \frac{2}{3}\sigma \\ 0.85 & \text{if } dist > \frac{2}{3}\sigma \text{ and } dist \leq \sigma \\ \langle 0.8, 0.1 \rangle & \text{if } dist > \sigma \text{ and } dist \leq 3\sigma \\ 0.05 & \text{if } dist > 3\sigma \text{ OR if } minCondition \text{ is not met} \end{cases}$$

(b) Calculate the final disease likelihood using weighted mean of all previous likelihoods.

2. Classify the image into the disease class with the highest likelihood.

The required minimal condition *minCondition* for each disease, as well as conditions for a healthy fingerprint or an unknown disease, are listed here:

- **Acrodermatitis**: more than 40 "cheetah" spots.
- **Atopic eczema**: more than 4 lines, 2 "cheetah" spots and 3 disruptions.
- **Psoriasis**: more than 3 white spots, 2 lines, 10 "cheetah" spots and 2 disruptions.
- **Verruca vulgaris**: more than 1 white spot.
- **Unknown**: provided that all disease likelihoods are less than 40%.
- **Healthy**: provided that the damage percentage is lower than 10% and the image had not been classified as verruca vulgaris.

Chapter 8

Experiments and Results

8.1 Damage Localizer Results

Each of the three detection methods separately provides interesting outputs, but it is their connection that makes the resulting application so notable. Thanks to the connection, very satisfactory results have been achieved for locating the damaged areas.

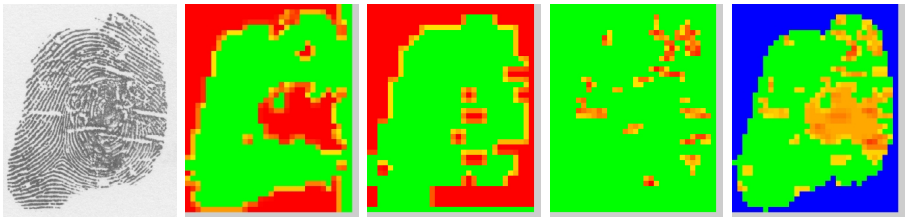

Figure 8.1: Example of the pipeline of `StatusMaps` and the final distribution of damage in the image (Atopic eczema). Green color marks the healthy areas, blue color highlights the background and for the damaged areas a scale from yellow to red is used. Yellow stands for minor damage, whereas red implies extremely damaged places.

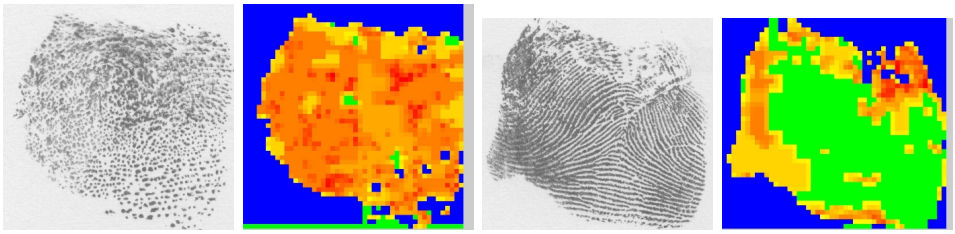

Figure 8.2: Damage detection results. Green color marks the healthy areas, blue color highlights the background and for the damaged areas a scale from yellow to red is used. Yellow stands for minor damage, whereas red implies extremely damaged places.

Table 8.1: Rejected and accepted samples.

	TP	FN	FP	TN
Acrodermatitis	12	18	103	478
Atopic eczema	134	289	25	163
Verruca vulgaris	23	17	314	257
Total	611	611	611	611

Table 8.2: Classifier accuracy measures.

	FAR	FRR	F1	ACC
Acrodermatitis	0.1394	0.6667	0.1655	0.8347
Atopic eczema	0.1968	0.7021	0.4300	0.4533
Psoriasis	0.3408	0.7373	0.1956	0.5827
Verruca vulgaris	0.2329	0.5000	0.2073	0.7496

8.2 Classifier Accuracy

The Classifier itself is ready to be further extended and improved. It relies on the detection results. So far, the following accuracy measures have been computed: FAR (*False Accept Rate*) and FRR (*False Reject Rate*) [20], ACC (accuracy) and F1 score [20] - see Table 8.2.

611 fingerprint images from dactyloscopic cards from the database were used for the test. Table 8.1 shows the numbers of fingerprint images that were correctly/incorrectly classified. TP (*True Positives*) = number of positives that were correctly accepted, FN (*False Negatives*) = number of negatives that were incorrectly rejected, FP (*False Positives*) = number of positives that were incorrectly accepted and TN (*True Negatives*) = number of negatives that were correctly rejected.

The classification accuracy reached high values for for acrodermatitis (83.5%) and verruca vulgaris recognition (75.0%), whereas it was lower for atopic eczema (45.3%) and psoriasis (58.3%). Better performance could be gained by improving the classification decision rules, as well as coming up with new types of features detection.

8.3 Possible Extensions and Enhancements

The three methods introduced in this work provide a very good foundation for future research and have great potential be further extended, so that they can serve in real-world applications.

Skin disease detection using image recognition algorithms is a complex task, however. What is more, this is a completely new and unique project, so there are no existing detection methods yet. Therefore, the procedures described in this Bachelor's thesis can undoubtedly be further enhanced so that in the future the detection and classification pipeline performs even better.

The major areas in which the program could be enhanced are:

- **Damage removal**: The greatest potential lies in using these methods to create a program that would automatically remove the damage found in the fingerprint and leave only the healthy parts.
- **Damage repair**: In some cases, it would be possible to even repair some of the damaged areas (e.g. connect ridges, disrupted by a crack in the skin).
- **Histogram analysis**: There is a big chance to improve the histogram validation process and extend the results from bare "damaged/healthy" to a more precise decimal scale from 0 to 1. This could be done by upgrading the validity tests, as well as by enriching the algorithm with some statistical calculations.
- **Histogram analysis preprocessing**: By improving the preprocessing steps so that the input images have roughly the same input properties (contrast, brightness), the method will perform well also on lower-quality, especially dark, images.
- **Flood fill**: The preprocessing steps can be further refined to reach better results.
- **Speed**: The detection algorithms can be optimized so that the pipeline runs faster.
- **Other sensors**: So far, the application was tested on samples from dactyloscopic cards only. The algorithms can be adapted to other types of sensors as well.

Chapter 9

Conclusion

This thesis deals with the detection of skin diseases from fingerprint images. The goal was to design and develop methods that would locate the damaged areas from the fingerprint image, and based on their specific properties, determine the possible type of disease present in the fingerprint image. This objective was met and a classifier for 4 types of skin diseases was developed: *acrodermatitis*, *atopic eczema*, *psoriasis* and *verruca vulgaris*.

Before the methods were designed, the faculty's database of fingerprint images affected by skin disease was thoroughly analyzed and, based on this foundation, possible algorithms for damaged area detection were tested, including the Hough detection for lines and circles, which was rejected for its inaccuracy. In the end, the following methods were implemented: Detection from Block Orientation Field, Histogram Analysis Method and the Flood Fill Method. The best results were achieved by connecting the methods together using a special data structure, `StatusMap`.

The Classifier makes decisions based on statistics that resulted from testing the algorithms on the whole fingerprint database. Using the methods described in this work, the program reached an accuracy of 83.5% for acrodermatitis, 45.3% for atopic eczema, 58.3% for psoriasis and 75.0% for verruca vulgaris.

The resulting program is a GUI application that enables the user to load an image, adjust the processing pipeline, and view and save the results. It can be used as an analytical tool for future researchers.

There is a great potential for improvements and enhancements, and it is assumed that the research will continue. There are opportunities for the results of this research to be used in real-life applications in the future, such as medical applications or programs for police and security purposes.

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Appendices

Appendix A

Experimental results

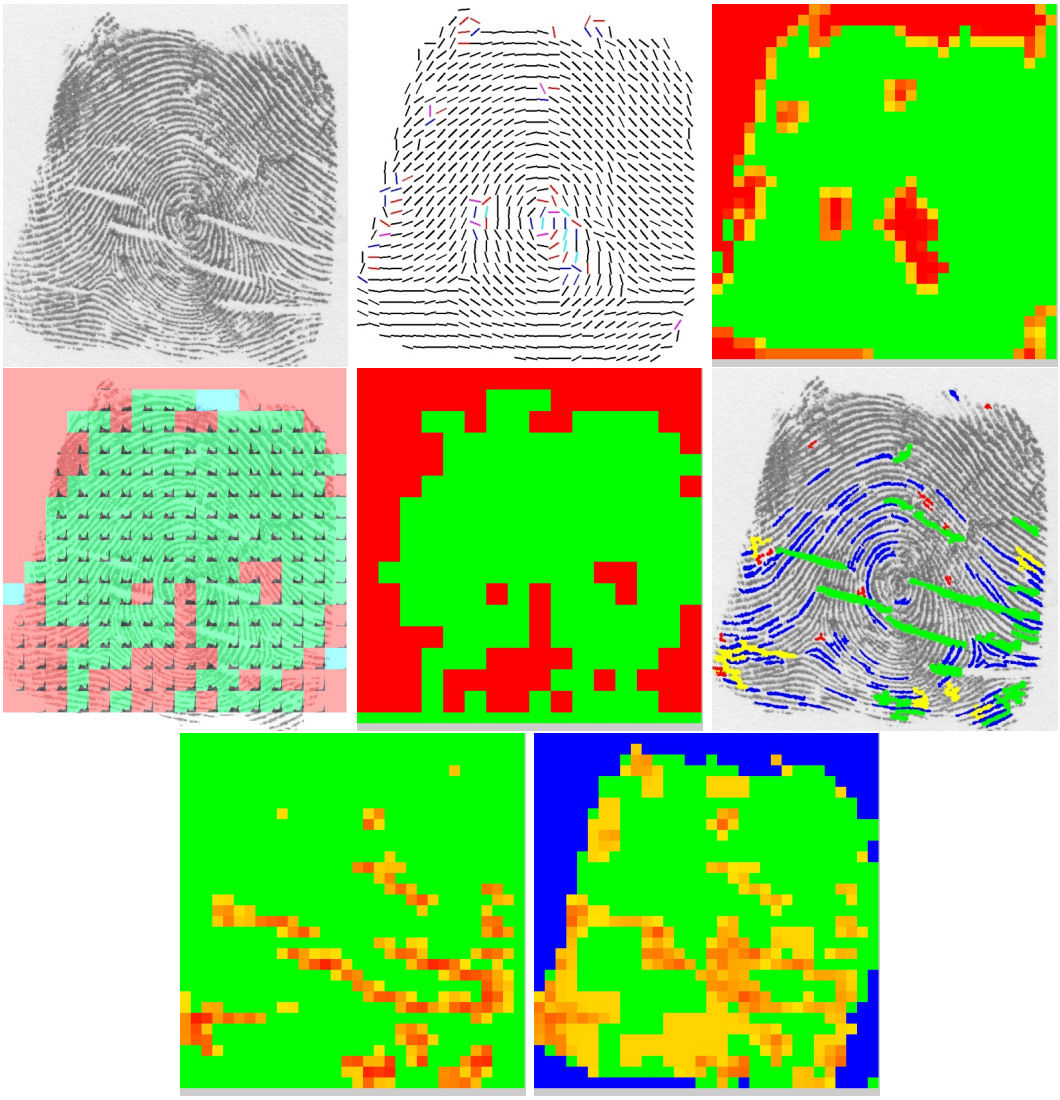

Figure A.1: Experimental results: *atopic eczema*.

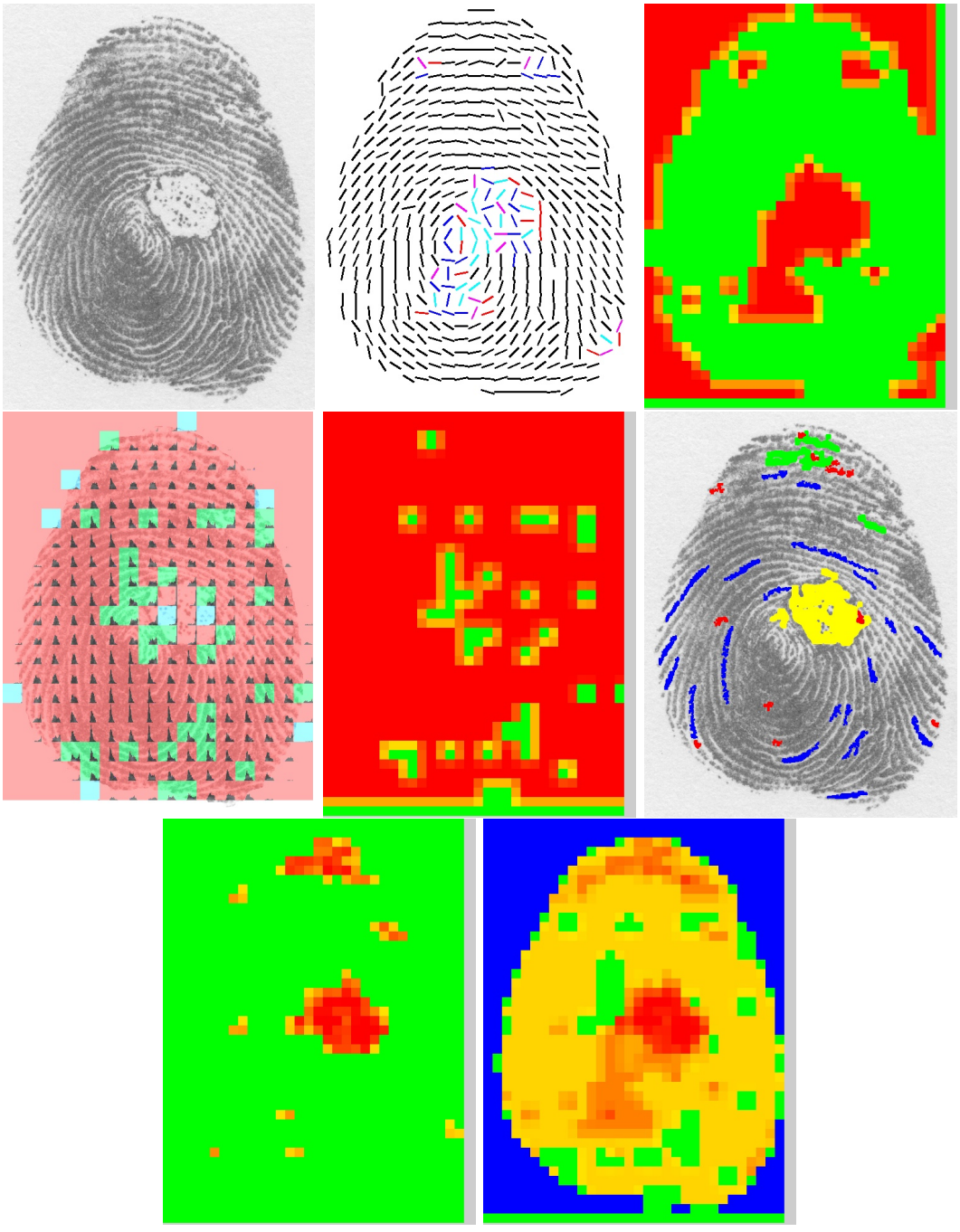

Figure A.2: Experimental results: *verruca vulgaris*.

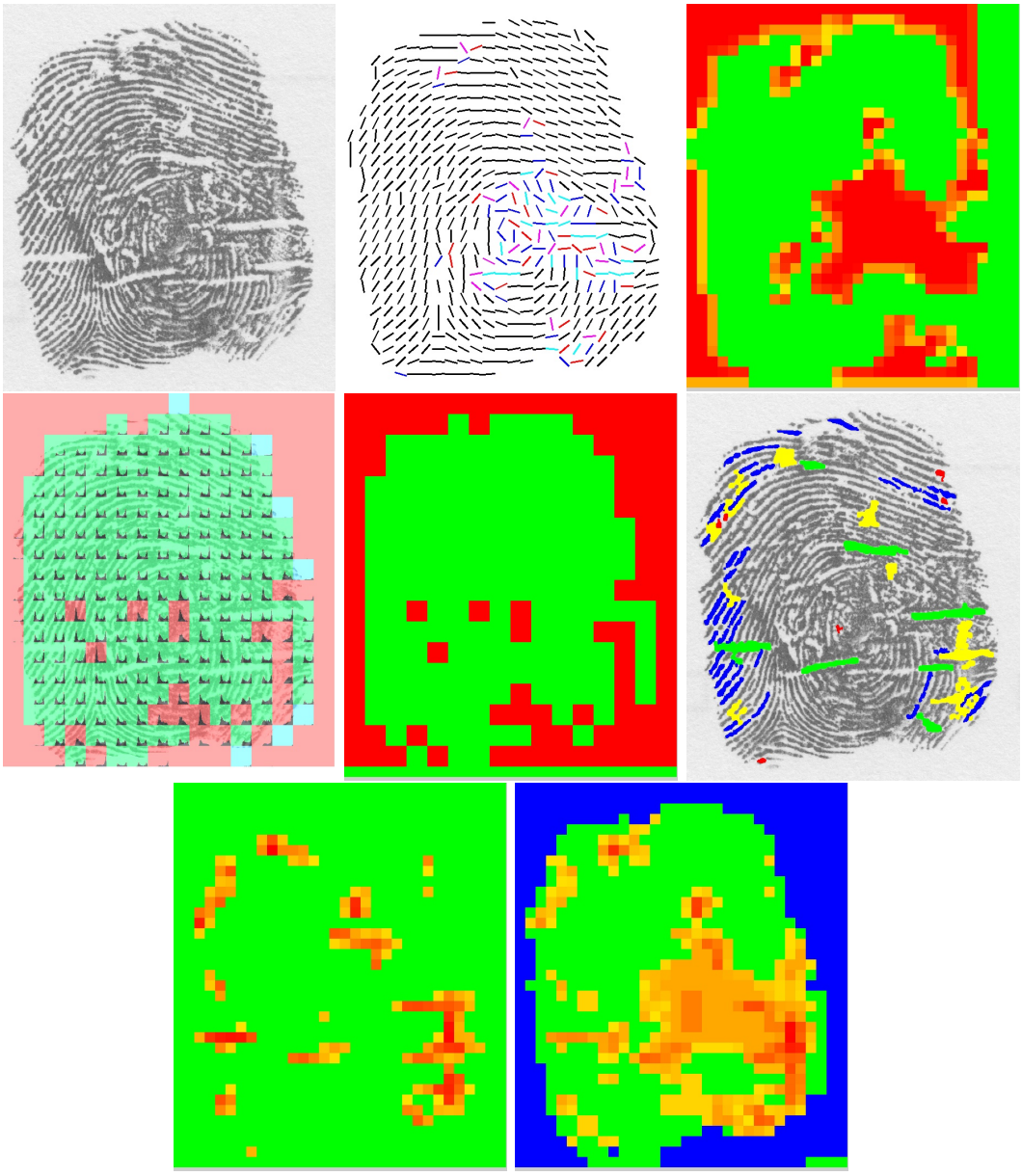

Figure A.3: Experimental results: *atopic eczema*.

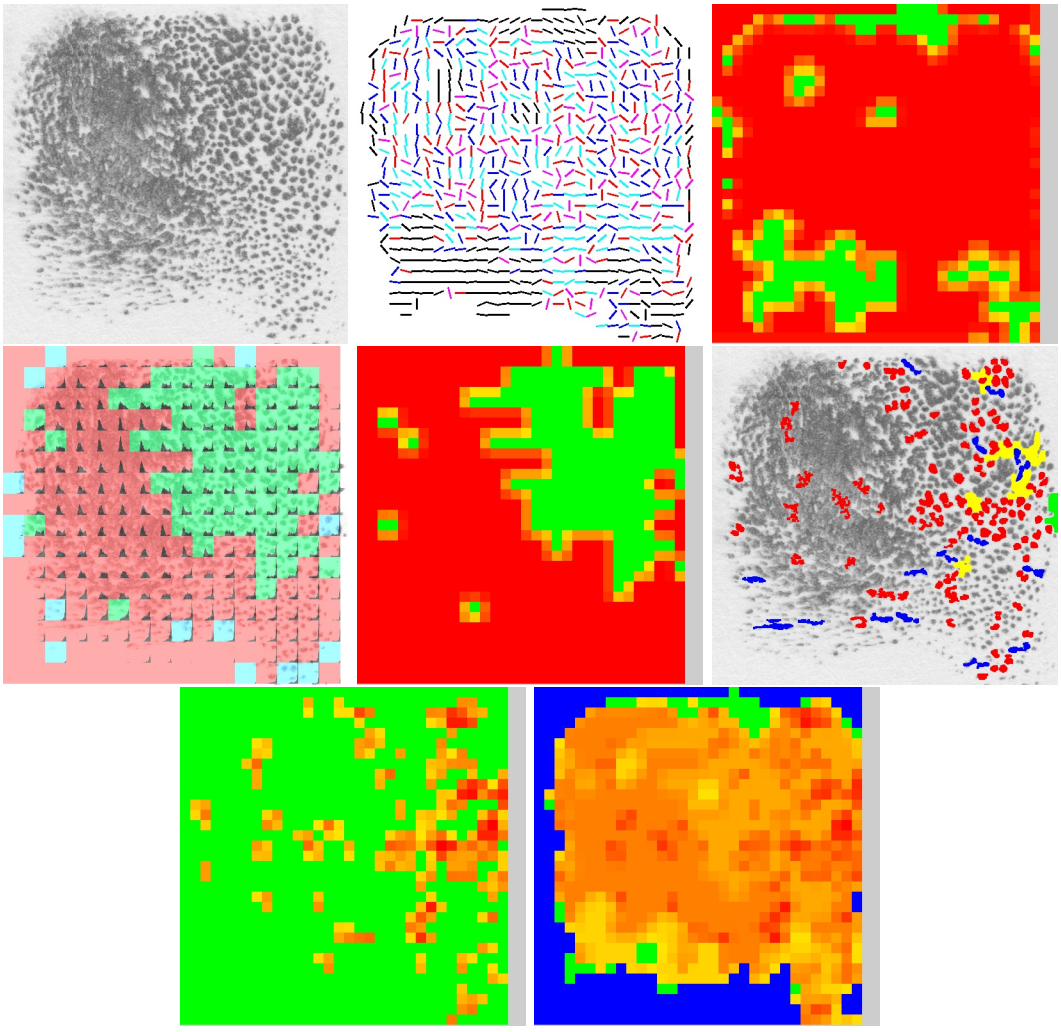

Figure A.4: Experimental results: *acrodermatitis*.

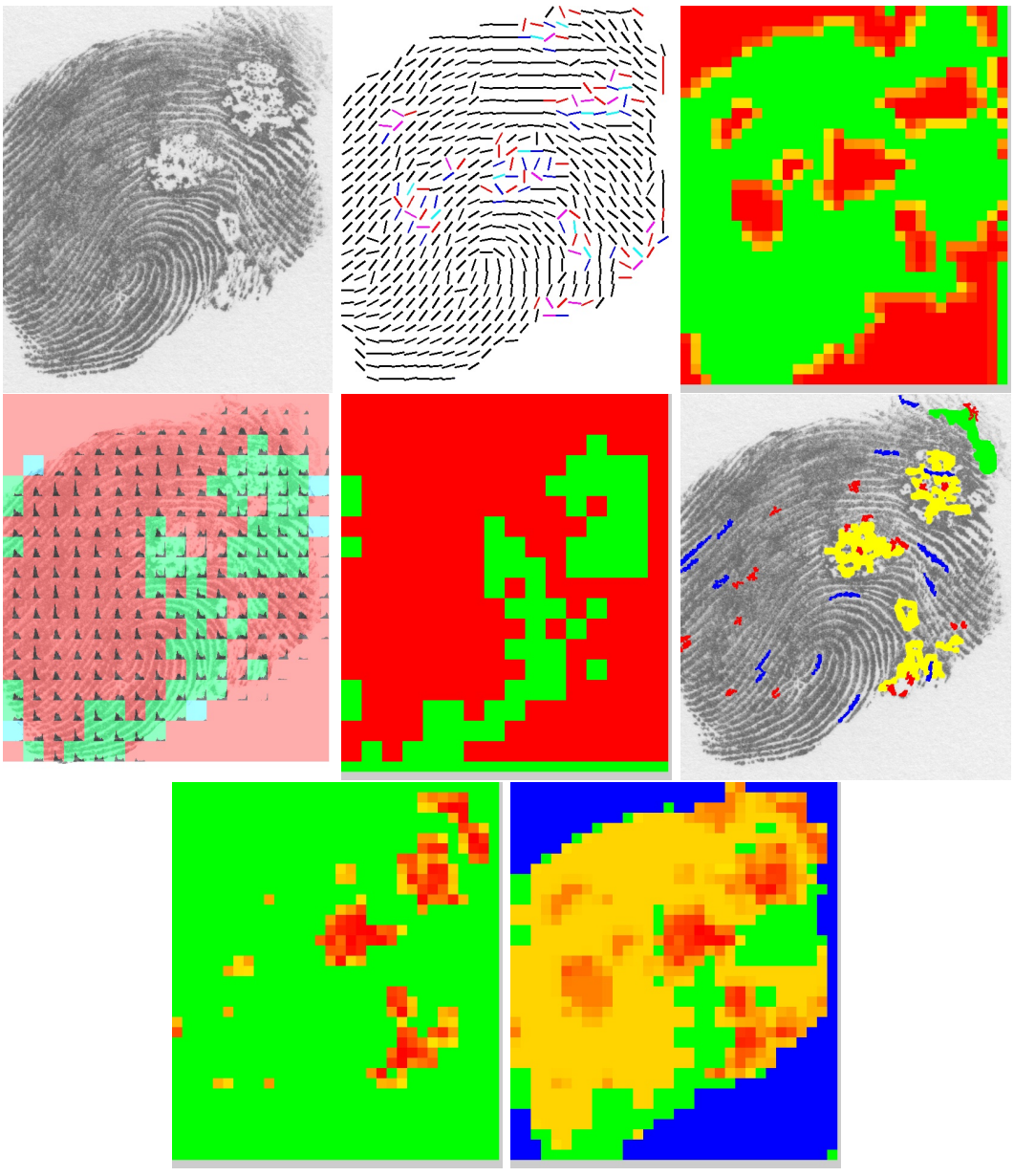

Figure A.5: Experimental results: *verruca vulgaris*.

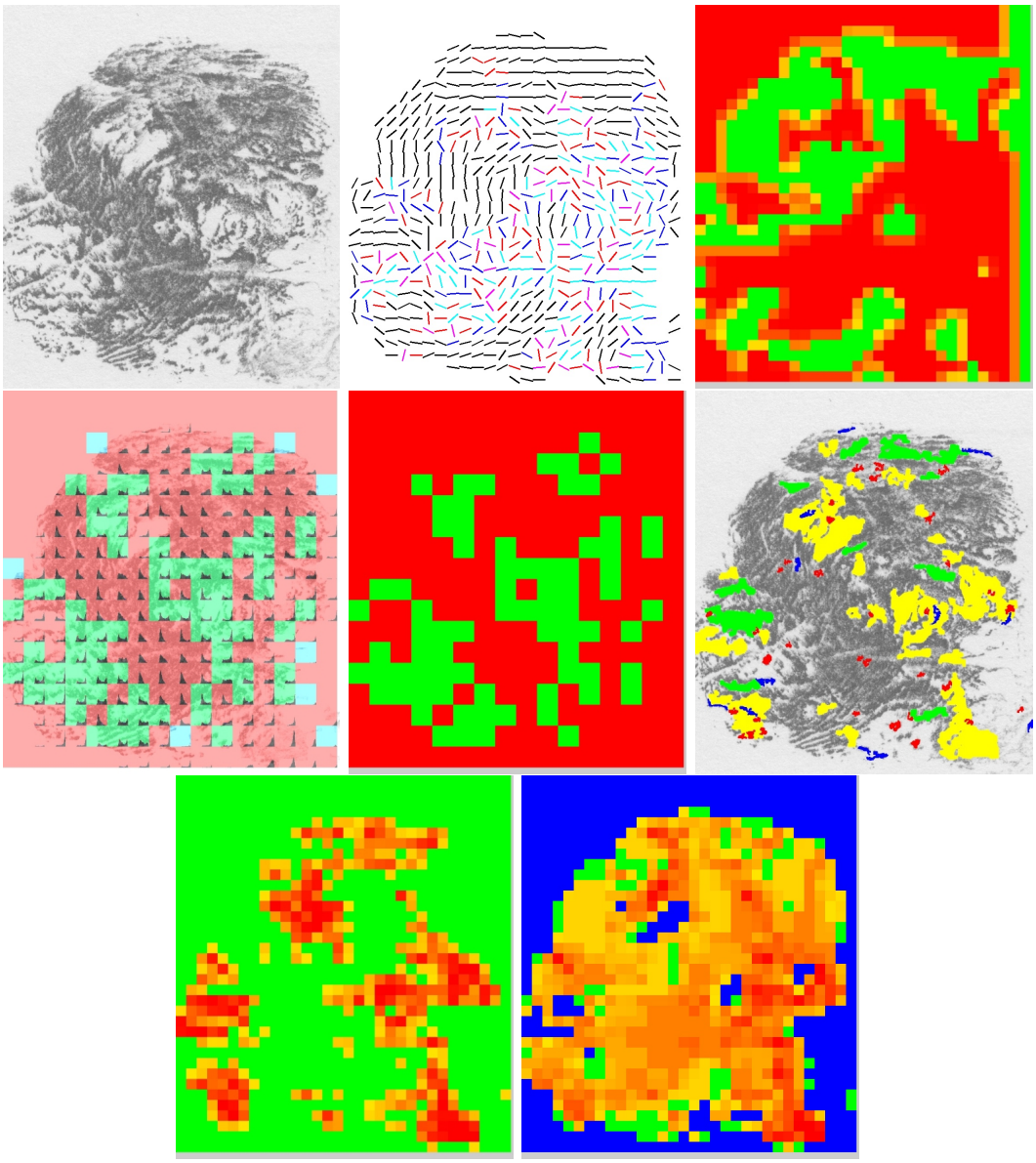

Figure A.6: Experimental results: *psoriasis*.