

Deep Learning Based Person Authentication Hand Radiographs

^[1] E.DilipKumar, R.Praveen Kumar

^{[1][2]} Department of MCA, Dhanalakshmi Srinivasan college of engineering and Technology

^[1] mailtodilip82@gmail.com, ^[2] praveenkumarr.mca2021@dscet.ac.in

Abstract: Authentication is the process of automatically recognizing the correct person. Presently, the biometric identification systems are based on static features like face[2], iris[3], palm print[4], voice[5] and fingerprint impression of the user, which mostly remains unchanged over time. The performance of a biometric identification system is measured based on accuracy, efficiency, security, and privacy. Biometric systems are a combination of multiple sensors, multiple algorithms, and numerous instances, making it more accurate, reliable, secure, and robust[6]. Identifying an injured person is challenging in disasters like tsunamis and earthquakes and catastrophic accidents. In such cases hand radiographs may be considered. Because bones cannot be easily damaged. The existing method uses KNN (K-Nearest Neighbor) classifier[8]. It consists of training and testing stage. In training stage, CNN is applied which includes mainly convolution layer, ReLU layer and Max pooling layer. The proposed method uses CNN classifier. It consists of training and testing stage.

1. INTRODUCTION

CNN is applied which includes mainly convolution layer, ReLU layer and Max pooling layer. In the proposed work Person Authentication is performed with the hand radiographs using Image processing and deep learning concept[1]. Three-layered convolutional deep-learning architecture is used for the pre-processing, feature extraction and max pooling layer. An individual's identity is ascertained using these three layers[7].

CNN is inspired by the biological phenomenon of the animal visual cortex, which shows the connectivity pattern between different neurons. CNN has a wide range of applications such as image processing, video processing, speech processing, and natural language processing. CNN consists of four significant steps, such as convolution layer, rectified linear unit (ReLU), maximum pooling layer, and fully connected layer.

In the convolution layer, an image is multiplied by filter kernel, which may have some negative values. These negative values bring the non-linearity in the image. The non-linearity is then removed by using the rectified linear unit layer by converting all the negative values to zero using where, I_{ReLU} is the ReLU layer image and I_{conv} is the convolutional layer image. The ReLU layer output size is $200 \times 200 \times 3$, which is equal to the size of the convolution layer output. The output of the ReLU layer is given to max pooling layer.

Pooling is used for the minimization of the computing cost by reducing the dimension of the ReLU layer output. Pooling is also used to retain the position and rotational invariant features of an image. There are two types of pooling methods: Maximum and Average pooling. In maximum pooling, the maximum value of the given window is selected, while in average pooling, the average value of the window is selected. Unlike average pooling, maximum pooling suppresses the noise in the image along with feature reduction. Pooling is also used to maintain the localization of the shape of the local object in the image. The window size of 2×2 is selected for maximum pooling, which reduced the size to exactly half of the ReLU layer ($100 \times 75 \times 6$). The larger window size for the maximum pooling may result in the fine local information of the image.

A binary image is a digital image that has only two possible values for each pixel. Typically the two colors used for a binary image are black and white though any two colors can be used. The color used for the object(s) in the image is the foreground color while the rest of the image is the background color. Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit (0 or 1).

A gray scale Image is digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray (0-255), varying from black (0) at the weakest intensity to white (255) at the strongest. Gray scale images are distinct from one-bit black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called bi-level or binary images). Gray scale images have many shades of gray in between. Gray scale images are also called monochromatic, denoting the absence of any chromatic variation. Gray scale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a

given frequency is captured. But also they can be synthesized from a full color image.

Authentication is the process of automatically recognizing the correct person. Presently, the biometric identification systems are based on static features like face[2], iris[3], palm print[4], voice[5] and fingerprint impression of the user, which mostly remains unchanged over time. The performance of a biometric identification system is measured based on accuracy, efficiency, security, and privacy. Biometric systems are a combination of multiple sensors, multiple algorithms, and numerous instances, making it more accurate, reliable, secure, and robust[6]. Identifying an injured person is challenging in disasters like tsunamis and earthquakes and catastrophic accidents. In such cases hand radiographs may be considered. Because bones cannot be easily damaged.

The existing method uses KNN (K-Nearest Neighbor) classifier[8]. It consists of training and testing stage. In training stage, CNN is applied which includes mainly convolution layer, ReLU layer and Max pooling layer. The proposed method uses CNN classifier. It consists of training and testing stage.

PROJECT DESCRIPTION:

This project 'Deep learning based Person Authentication using Hand Radiographs' is essentially a pattern recognition system that makes use of biometric traits to recognize individuals. The texture of the hand radiographs of different individuals has been proven to be distinctive even among identical twins.

OBJECTIVES OF THE PROJECT:

The objective of the project is to Authenticate a Person using Deep Learning. Deep-learning architecture has three layers, they are pre-processing, feature extraction and max pooling layer. An individual's identity is ascertained using these three layers.

SYSTEM ANALYSIS

INTRODUCTION:

Design is the first step in the development phase for any techniques and principles for the purpose of defining a device, a process or system in sufficient detail to permit its physical realization. Once the software requirement have been analyzed and specified the software design involving three technical activities-design, coding, implementation and testing that are required to build and verify the software.

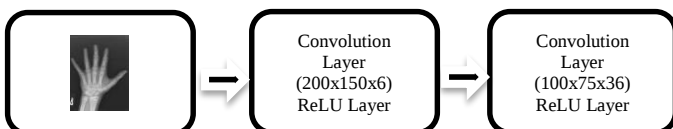
SYSTEM STUDY:

The specific details of the project are specified by the person authentication using hand radiographs. In this document, various steps involved in the existing system process have been explained. In the project have the used to base on hand radiographs using a deep learning. Three-layered convolutional deep-learning architecture is used for the pre-processing, feature extraction and max pooling layer. An individual's identity is ascertained using these three layers.

EXISTING SYSTEM:

The logical module of the existing method using KNN classifier. It consists of training and testing stage. In training stage, CNN is applied which includes mainly convolution layer, ReLU layer and Max pooling layer.

The existing method using three CNN layers. The first CNN layer resize the image to 200x150 and then passes it to ReLU layer. The 6x6 matrix is used ReLU layer (200x150x6). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 100x75x6. The second CNN layer resize the image to 100x75x36 and then passes it to ReLU layer. The 6x6 matrix is used ReLU layer (100x75x36). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 50x37x36. The last CNN layer resize the image to 50x37x216 and then passes it to ReLU layer. The 6x6 matrix is used ReLU layer (50x37x216). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 25x18x216. Finally the hand radiograph image is converted to 97200x1 in the fully connected layer. The image derived from the fully connected layer is used in the KNN classifier. Finally the identity of the individual is authenticated or unauthenticated is shown in figure 2.3.



PROPOSED SYSTEM:

The logical module of the proposed method using CNN classifier. It consists of training and testing stage. CNN is applied which includes mainly convolution layer, ReLU layer and Max pooling layer.

The proposed method using five CNN layers. The first CNN layer resize the image to 200x200 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (200x200x3). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 100x100x3. The second CNN layer resize the image to 100x100x9 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (100x100x9). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 50x50x9. The third CNN layer resize the image to 50x50x27 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (50x50x27). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 25x25x27. The fourth CNN layer resize the image to 25x25x81 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (25x25x81). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 13x13x81. The last CNN layer resize the image to 25x25x243 and then passes it to ReLU layer. The 6x6 matrix is used ReLU layer (25x25x243). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 13x13x243.

Finally the hand radiograph image is converted to 41067x1 in the fully connected layer. The image derived from the fully connected layer is used in the CNN classifier. Finally the identity of the individual is authenticated or unauthenticated is shown in

2.5 MODULE DESCRIPTION:

The project includes five processing modules, they are:

1. Loading of data set
2. Pre-Processing
3. Feature extraction
4. Trained and test data
5. Output

2.5.1 LOADING OF DATA SET

The input data set is downloaded from the kaggle website. The downloaded data set includes four thousand sixty four rows and four columns. From this only seventy hand radiograph data sets were extracted.

2.5.2 PRE-PROCESSING

Pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of images like resize, hand segmentation, background removal, rotation and normalization are classified among pre-processing methods. This project uses resize and normalization process method.

2.5.3 FEATURE EXTRACTION

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data. ReLU Layer and Maxpooling layer is used in feature extraction module.

2.5.4 TRAINED AND TEST DATA

Train/Test is a method to measure the accuracy of your model. It is called Train/Test because you split the data set into two sets: a training set and a testing set. Example 80% for training and 20% for testing.

2.5.5 OUTPUT

The hand radiograph image in the output module is available in two format. One is authorized person and another one is unauthorized person. Authorized person has 30 images and unauthorized person has 40 images.

2.6 CONCLUSION

This chapter outlines the total system analysis performed with respect to user system specification, System Study based project specification Requirement Analysis, and the Modules Proposed. Further in the next chapter, the system design and development are addressed.

SYSTEM DESIGN AND DEVELOPMENT**3.1 INTRODUCTION**

The system analysis follows system design with two major aspects namely, i) Logical design and ii) physical design. Following the design, the development of the system based on coding design using the chosen software technologies is carried out.

3.2 LOGICAL DESIGN

The logic design of the system is conceived and represented using some standard design elements such as algorithmic procedures, Block Diagram, Sequence Diagram and etc.

3.2.1 BLOCK DIAGRAM

A Block diagram is a static structural diagram that shows system components, their contents and interfaces and relationships.

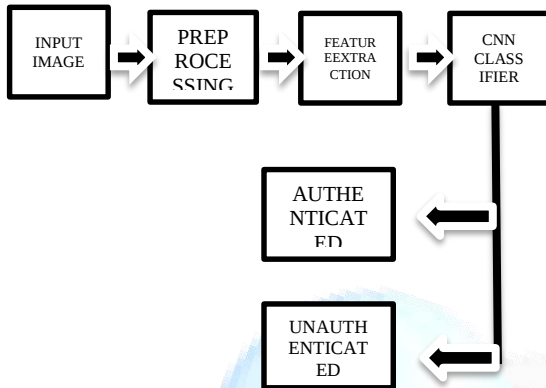


Figure 3.2.1 Block Diagram

The above diagram illustrates the modules relationship in the project is shown in figure 3.2.1.

3.3 PHYSICAL DESIGN

The physical design contains the dataset design (tables & images).

3.4 DATA SET

The data set is downloaded from the kaggle website (<http://www.kaggle.com>).

The downloaded data set includes four thousand sixty four rows and four columns. From this only seventy hand radiograph data sets were extracted. Because they are all PNG (Portable Network Graphics) file. The PNG File format is widely used on website to display high-quality digital image. A PNG File is used by many editing programs and software is shown in table 3.4.

Table 3.4: Data set image format table

S. NO.	IMAGE NUMBER	TYPE	SIZE
1	4360	PNG File	302 KB
2	4361	PNG File	395 KB
3	4362	PNG File	2,813 KB
4	4363	PNG File	316 KB
5	4364	PNG File	266 KB
6	4365	PNG File	327 KB
7	4366	PNG File	282 KB
8	4367	PNG File	248 KB
9	4368	PNG File	372 KB
10	4369	PNG File	2,073 KB
11	4370	PNG File	422 KB
12	4371	PNG File	1,192 KB
13	4372	PNG File	338 KB
14	4373	PNG File	242 KB
15	4374	PNG File	303 KB
16	4375	PNG File	254 KB
17	4376	PNG File	342 KB
18	4377	PNG File	1,271 KB
19	4378	PNG File	286 KB

20	4379	PNG File	3,258 KB
21	4380	PNG File	1,295 KB
22	4381	PNG File	926 KB
23	4382	PNG File	193 KB
24	4383	PNG File	322 KB
25	4384	PNG File	778 KB
26	4385	PNG File	226 KB
27	4386	PNG File	215 KB
28	4387	PNG File	299 KB
29	4388	PNG File	1,155 KB
30	4389	PNG File	169 KB
31	4520	PNG File	3,196 KB
32	4521	PNG File	1,313 KB
33	4522	PNG File	2,132 KB
34	4523	PNG File	1,691 KB
35	4524	PNG File	1,259 KB
36	4525	PNG File	1,199 KB
37	4526	PNG File	1,031 KB
38	4527	PNG File	304 KB
39	4528	PNG File	1,764 KB
40	4529	PNG File	355 KB
41	4530	PNG File	2,349 KB
42	4531	PNG File	1,127 KB
43	4532	PNG File	277 KB
44	4533	PNG File	1,649 KB
45	4534	PNG File	876 KB
46	4535	PNG File	182 KB
47	4536	PNG File	1,080 KB
48	4537	PNG File	320 KB
49	4538	PNG File	1,330 KB
50	4539	PNG File	1,325 KB
51	4540	PNG File	3,454 KB
52	4541	PNG File	3,639 KB
53	4542	PNG File	1,763 KB
54	4543	PNG File	1,066 KB
55	4544	PNG File	175 KB
56	4545	PNG File	294 KB
57	4546	PNG File	254 KB
58	4547	PNG File	570 KB
59	4548	PNG File	288 KB
60	4549	PNG File	3,308 KB
61	4550	PNG File	3,474 KB
62	4551	PNG File	3,375 KB

63	4552	PNG File	1,107 KB
64	4553	PNG File	170 KB
65	4554	PNG File	196 KB
66	4555	PNG File	1,224 KB
67	4556	PNG File	239 KB
68	4557	PNG File	244 KB
69	4558	PNG File	227 KB
70	4559	PNG File	291 KB

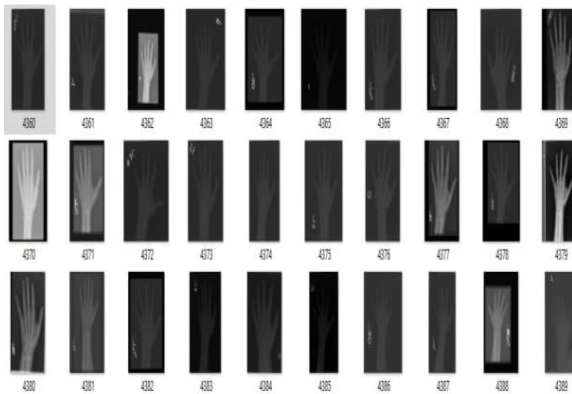


Figure 3.4 Sample images of hand radiographs from the dataset

3.5 MODULES:

The project includes five processing modules, they are:

1. Loading of data set
2. Pre-Processing
3. Feature extraction
4. Trained and test data
5. Output

3.5.1 LOADING OF DATA SET

The input data set is downloaded from the kaggle website. The downloaded data set includes four thousand sixty four rows and four columns. From this only seventy hand radiograph data sets were extracted. Because they are all PNG (Portable Network Graphics) file. The PNG File format is widely used on website to display high-quality digital image is shown in figure3.5.1.1, 3.5.1.2 and 3.5.1.3.

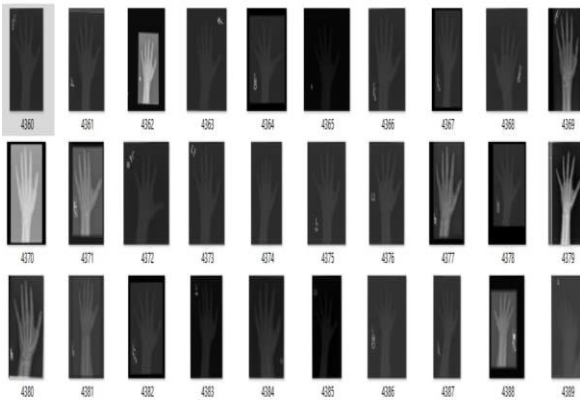


Figure 2.5.1.3 PNG File format

3.5.2 PRE-PROCESSING

Pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of images like resize, hand segmentation, background removal, rotation and normalization are classified among pre-processing methods.

In the preprocessing method, the Kera's library is imported from the tensor flow software. A convolutional 2D layer is imported from an imported Kera's library. Then the numpy library is imported. The numpy is used to convert the downloaded image into an array. This project uses resize and normalization process method. The hand radiographs image is resized into 200x200 as shown in figure 3.5.2. This is because all hand radiographs images should be the same size. A hand radiograph image can be processed in ReLU and maxpooling layers only if they are of the same size.

```
model = tf.keras.models.Sequential([
    # Note the input shape is the desired size of the image 200x 200 with 3 bytes color
    # The first convolution
    tf.keras.layers.Conv2D(16, (3,3), activation='relu', input_shape=(200, 200, 3)),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The second convolution
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The third convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fourth convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fifth convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # Flatten the results to feed into a dense layer
    tf.keras.layers.Flatten(),
    # 128 neuron in the fully-connected layer
    tf.keras.layers.Dense(128, activation='relu'),
    # 5 output neurons for 5 classes with the softmax activation
    tf.keras.layers.Dense(5, activation='softmax')
])
```

Figure 3.5.2 Code for working of CNN algorithm

3.5.3 FEATURE EXTRACTION

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.

ReLU Layer and Maxpooling layer is used in feature extraction module. Maxpooling layer is imported from Kera's library. There are five types feature extraction methods for hand radiograph image. They are radius-ulna, carpal, metacarpal, phalanges and epiphysis. The ReLU (Rectified Linear Unit) is not a separate component of the convolutional neural network process. The ReLU layer is to improve the nonlinearity of the image's pixel data. Maxpooling returns the maximum value from the portion of the image covered by the kernel.

3.5.4 TRAINED AND TEST DATA

Train/Test is a method to measure the accuracy of your model. It is called Train/Test because the splitted data set is into two sets: a training set and a testing set. Example 80% for training and 20% for testing.

Epoch= total sample / batch size

In the training stage a hand radiographs image is divided into 30 epochs. Each epoch is trained separately based on above formula is shown in figure 3.5.4.1. Each epoch to gives accuracy and loss and it is shown in figure 3.5.4.2. The graph is drawn to predict the accuracy and loss of calculated epoch. Accuracy and loss is drawn based on epoch versus time duration. Accuracy graph interpreted it is positively correlated which implied if epoch increases with duration. Loss graph interpreted it is negatively correlated which stands the epoch decreases while duration increases is shown in figure 3.5.4.3.

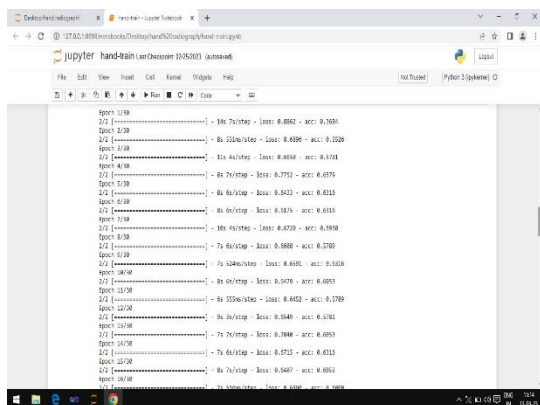


Figure 3.5.4.2 Code for training epoch



Figure 3.5.4.3 Graph for Training Accuracy and Training Loss

A hand radiograph image path is copied during the test stage. Converts the copied image to 200x200. The transformed image is converted to array and then the hand radiograph image is sent to the output module for better quality is shown in figure 3.5.4.4.

```
In [11]: # Make a prediction on the test image
test_image = image.load_img('dataset\authorized person\4373.png', target_size=(200, 200))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
test_image /= 255.
result = model.predict(test_image)

# Print the predicted class
if result[0][0] > result[0][1]:
    label='Authorized person(jen)'
else:
    label='Unauthorized person'

1/1 [=====] - 8s 138ms/step
```

Figure 3.5.4.4 Code for testing data

3.5.5 OUTPUT

The hand radiograph image in the output module is available in two format. One is authorized person and another one is unauthorized person. Authorized person has 30 images and unauthorized person has 40 images is shown in figure 3.5.5.1 and 3.5.5.2.

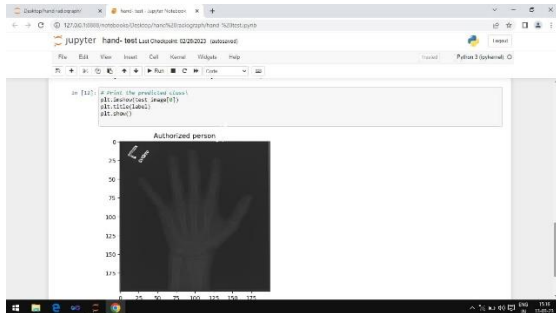


Figure 3.5.5.1 Output of Authorized person

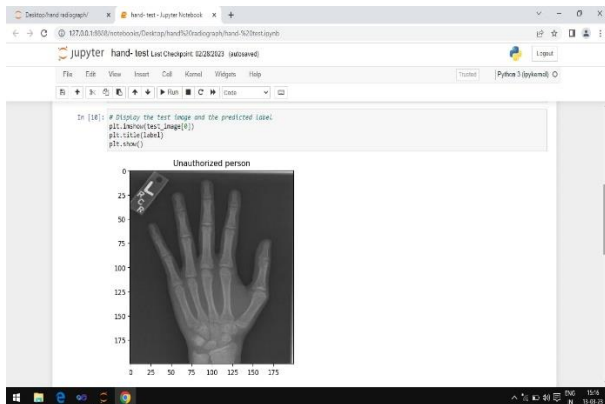


Figure 3.5.5.2 Output for Unauthorized person

4.2 SYSTEM IMPLEMENTATION

In the project have the used to base on hand radiographs using a deep learning. Three-layered convolutional deep-learning architecture is used for the pre-processing, feature extraction and max pooling layer. An individual's identity is ascertained using these three layers.

4.2.1 CONVOLUTION NEURAL NETWORK

CNN is inspired by the biological phenomenon of the animal visual cortex, which shows the connectivity pattern between different neurons. CNN has a wide range of applications such as image processing, video processing, speech processing, and natural language processing. CNN consists of four significant steps, such as convolution layer, rectified linear unit (ReLU), maximum pooling layer, and fully connected layer. The architecture of the CNN single layer is shown in Fig.4.2.1.

The hand radiograph image obtained in this project is used five convolution layer. The hand radiograph image is converted to first layer 200x200x3, the second layer 100x100x9, third layer 50x50x27, fourth layer 25x25x81 and finally 25x25x243. The hand radiograph image is more accurate enhances by using five convolution layer.

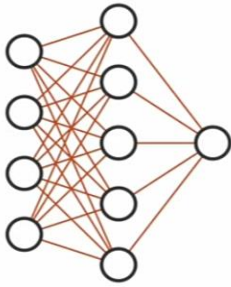


Figure 4.2.1 The architecture of the CNN Layer

4.2.2 ReLU LAYER

In the convolution layer, an image is multiplied by filter kernel, which may have some negative values. These negative values bring the non-linearity in the image. The non-linearity is then removed by using the rectified linear unit layer by converting all the negative values to zero using where, IReLU is the ReLU layer image and Iconv is the convolutional layer image. The ReLU layer output size is 200X200X3, which is equal to the size of the convolution layer output. The output of the ReLU layer is given to max pooling layer. The hand radiograph image obtained in this project is used five ReLU layer. The hand radiograph image is converted to first layer 200x200x3, the second layer 100x100x9, third layer 50x50x27, fourth layer 25x25x81 and finally 25x25x243. The hand radiograph image is more accurate enhances by using five ReLU layer.

4.2.3 MAX POOLING LAYER

Pooling is used for the minimization of the computing cost by reducing the dimension of the ReLU layer output. Pooling is also used to retain the position and rotational invariant features of an image. There are two types of pooling methods: Maximum and Average pooling. In maximum pooling, the maximum value of the given window is selected, while in average pooling, the average value of the window is selected. Unlike average pooling, maximum pooling suppresses the noise in the image along with feature reduction. Pooling is also used to maintain the localization of the shape of the local object in the image. The window size of 2x2 is selected for maximum pooling, which reduced the size to exactly half of the ReLU layer (100x75x6). The larger window size for the maximum pooling may result in the fine local information of the image.

The hand radiograph image obtained in this project is used five maxpooling layer. The hand radiograph image is converted to first layer 100x100x3, the second layer 50x50x9, third layer 25x25x27, fourth layer 13x13x81 and finally 13x13x243. The hand radiograph image is more accurate enhances by using five maxpooling layer. Maxpooling returns the maximum value from the portion of the image covered by the kernel. Maxpooling is done to in part to help over fitting by providing an abstracted from the representation is shown in figure 4.2.3.

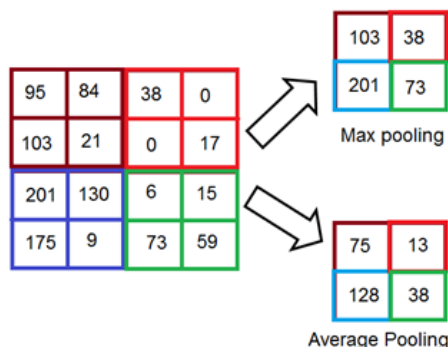


Figure 4.2.3 Max Pooling Layer

4.2.4 RESULT& DISCUSSON

The existing of the method using CNN applied in three layers. The performance of the system is evaluated based on percentage cross validation accuracy (0.6842) and loss (0.5404) is shown Table 4.2.4.1.

Table 4.2.4.1: Training of epoch for Existing system

Training Data (Epoch)	Training Period	Epoch Time	
		Accuracy	Loss
1/30	14 Seconds	0.5263	0.7092
2/30	8 Seconds	0.6842	0.6853
3/30	11 Seconds	0.5000	0.6847
4/30	8 Seconds	0.6316	0.6696
5/30	8 Seconds	0.5526	0.6640
6/30	8 Seconds	0.5781	0.7192
7/30	10 Seconds	0.5625	0.6721
8/30	7 Seconds	0.6053	0.6526
9/30	7 Seconds	0.5526	0.6823
10/30	8 Seconds	0.6316	0.6623
11/30	6 Seconds	0.5526	0.6730
12/30	9 Seconds	0.5625	0.6698
13/30	7 Seconds	0.5938	0.6563
14/30	7 Seconds	0.5526	0.6477
15/30	8 Seconds	0.6053	0.5842
16/30	7 Seconds	0.5526	0.7764
17/30	9 Seconds	0.6579	0.6327
18/30	9 Seconds	0.6562	0.5896
19/30	10 Seconds	0.6579	0.5957
20/30	8 Seconds	0.6316	0.5925
21/30	10 Seconds	0.7368	0.6275
22/30	9 Seconds	0.6719	0.6004
23/30	6 Seconds	0.7500	0.5477
24/30	9 Seconds	0.7188	0.5357
25/30	10 Seconds	0.7188	0.5021
26/30	10 Seconds	0.7031	0.5172
27/30	7 Seconds	0.7368	0.4997
28/30	7 Seconds	0.8158	0.3863
29/30	10 Seconds	0.8158	0.3766
30/30	5 Seconds	0.6842	0.5404

Cross Validation Accuracy = $\frac{\text{Correctly Recognition Samples} * 100}{\text{Total Number of Samples}}$

Each epoch to gives accuracy and loss the above formula. The graph is drawn to predict the accuracy and loss of calculated epoch. Accuracy and loss is drawn based on epoch versus time duration. Accuracy graph interpreted it is positively correlated which implied if epoch increases with duration. Loss graph interpreted it is negatively correlated which stands the epoch decreases while duration increases is shown in figure 4.2.4.2.



Figure 4.2.4.2 Graph for Training Accuracy and Training Loss from Existing system

Five CNN layers are used in this proposed method. So that the end of my project is more accurate. The performance of the system is evaluated based on percentage cross validation accuracy (0.8947) and loss (0.4038) is shown Table 4.2.4.3

Table 4.2.4.2: Training of epoch for Proposed system

Training Data (Epoch)	Training Period	Epoch Time	
		Accuracy	Loss
1/30	14 Seconds	0.3684	0.8862
2/30	8 Seconds	0.5526	0.6896
3/30	11 Seconds	0.5781	0.6650
4/30	8 Seconds	0.6579	0.7752
5/30	8 Seconds	0.6316	0.6433
6/30	8 Seconds	0.6316	0.6175
7/30	10 Seconds	0.5938	0.6720
8/30	7 Seconds	0.5789	0.6608
9/30	7 Seconds	0.6316	0.6591
10/30	8 Seconds	0.6053	0.6479
11/30	6 Seconds	0.5789	0.6452
12/30	9 Seconds	0.5781	0.6549
13/30	7 Seconds	0.6053	0.7040
14/30	7 Seconds	0.6316	0.6715
15/30	8 Seconds	0.6053	0.6407
16/30	7 Seconds	0.5000	0.6890
17/30	9 Seconds	0.5938	0.6523
18/30	9 Seconds	0.6406	0.6301
19/30	10 Seconds	0.6094	0.6460
20/30	8 Seconds	0.6562	0.5914
21/30	10 Seconds	0.7188	0.5914
22/30	9 Seconds	0.7500	0.5336
23/30	6 Seconds	0.7632	0.5615
24/30	9 Seconds	0.6562	0.6358
25/30	10 Seconds	0.7812	0.5366
26/30	10 Seconds	0.7500	0.5198
27/30	7 Seconds	0.8158	0.5354
28/30	7 Seconds	0.6579	0.5011
29/30	10 Seconds	0.8438	0.4333
30/30	5 Seconds	0.8947	0.4038

Cross Validation Accuracy = $\text{Correctly Recognition Samples} * 100 / \text{Total Number of Samples}$

Each epoch to gives accuracy and loss the above formula. The graph is drawn to predict the accuracy and loss of calculated epoch. Accuracy and loss is drawn based on epoch versus time duration. Accuracy graph interpreted it is positively correlated which implied if epoch increases with duration. Loss graph interpreted it is negatively correlated which stands the epoch decreases while duration increases is shown in figure 4.2.4.4,

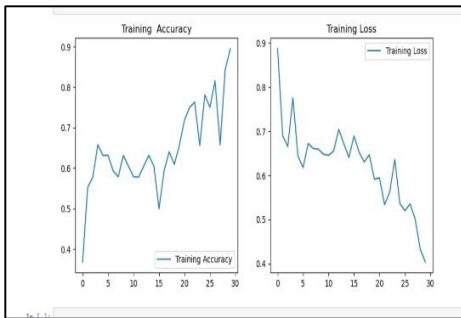


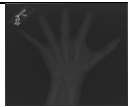
Figure 4.2.4.4 Graph for Training Accuracy and Training Loss from Proposed system

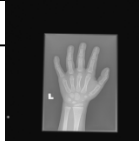
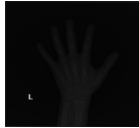
The output of the first convolution layer after the convolution of the original image of the first CNN layer resize the image to 200x200 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (200x200x3). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 100x100x3. The second CNN layer resize the image to 100x100x9 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (100x100x9). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 50x50x9. The third CNN layer resize the image to 50x50x27 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (50x50x27). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 25x25x27. The fourth CNN layer resize the image to 25x25x81 and then passes it to ReLU layer. The 3x3 matrix is used ReLU layer (25x25x81). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 13x13x81. The last CNN layer resize the image to 25x25x243 and then passes it to ReLU layer. The 6x6 matrix is used ReLU layer (25x25x243). The max pooling layer subtracts the maximum value from the ReLU layer and converts the image to 13x13x243. Finally the hand radiograph image is converted to 41067x1 in the fully connected layer. The image derived from the fully connected layer is used in the CNN classifier is shown in Table 4.2.5

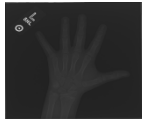
Table 4.2.5: Working of CNN layer

DEEP LEARNING LAYER	SUB- LAYER	FEATURE MAP SIZE
CNN Layer-I	Convolution Layer	200x200
	ReLU Layer	200x200x3
	Max Pooling Layer	100x100x3
CNN LayerII	Convolution Layer	100x100x9
	ReLU Layer	100x100x9
	Max Pooling Layer	50x50x9
CNN Layer-III	Convolution Layer	50x50x27
	ReLU Layer	50x50x27
	Max Pooling Layer	25x25x27
CNN Layer-IV	Convolution Layer	25x25x81
	ReLU Layer	25x25x81
	Max Pooling Layer	13x13x81
CNN Layer-V	Convolution Layer	25x25x243
	ReLU Layer	25x25x243
	Max Pooling Layer	13x13x243
Fully Connected Layer		41067x1

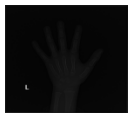
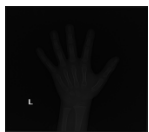
Finally the project will be detect hand print authorised person (or) unauthorised person is shown in Table 4.2.6
Table 4.2.6: Report for Pe

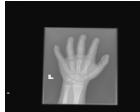
S. NO.	IMAGE NUMBER	IMAGE	SIZE	RESULT
1	4360		302 KB	Authorized Person
2	4520		395 KB	Unauthorized Person

3	4362		2813 KB	Authorized Person
4	4521		316 KB	Unauthorized Person
5	4364		266 KB	Authorized Person
6	4522		327 KB	Unauthorized Person
7	4523		282 KB	Unauthorized Person
8	4524		248 KB	Unauthorized Person
9	4368		372 KB	Authorized Person
10	4525		2,073 KB	Unauthorized Person
11	4370		422 KB	Authorized Person

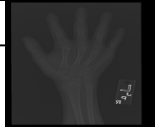
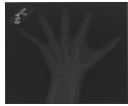
12	4371		1,192 KB	Authorized Person
13	4526		338 KB	Unauthorized Person
14	4527		242 KB	Unauthorized Person
15	4374		303 KB	Authorized Person
16	4528		254 KB	Unauthorized Person
17	4376		342 KB	Authorized Person
18	4529		1,271 KB	Unauthorized Person
19	4530		286 KB	Unauthorized Person
20	4379		3,258 KB	Authorized Person

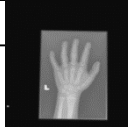
21	4531		295 KB	Unauthorized Person
22	4532		926 KB	Unauthorized Person
23	4533		193 KB	Unauthorized Person
24	4383		322 KB	Authorized Person
25	4384		778 KB	Authorized Person
26	4534		226 KB	Unauthorized Person
27	4386		215 KB	Authorized Person
28	4387		299 KB	Authorized Person
29	4535		1,155 KB	Unauthorized Person

30	4536		169 KB	Unauthorized Person
31	4385		3,196 KB	Authorized Person
32	4537		1,313 KB	Unauthorized Person
33	4561		2,132 KB	Authorized Person
34	4538		1,691 KB	Unauthorized Person
35	4539		1,259 KB	Unauthorized Person
36	4540		1,199 KB	Unauthorized Person
37	4563		1,031 KB	Authorized Person
38	4541		304 KB	Unauthorized Person

39	4565		1764 KB	Authorized Person
40	4542		355 KB	Unauthorized Person
41	4543		2,349 KB	Unauthorized Person
42	4566		1,127 KB	Authorized Person
43	4544		277 KB	Unauthorized Person
44	4545		1,649 KB	Unauthorized Person
45	4567		876 KB	Authorized Person
46	4546		182 KB	Unauthorized Person
47	4388		1,080 KB	Authorized Person
48	4569		320 KB	Authorized Person

49	4547		1,330 KB	Unauthorized Person
50	4548		1,325 KB	Unauthorized Person
51	4572		3,454 KB	Authorized Person
52	4549		3,639 KB	Unauthorized Person
53	4573		1,763 KB	Authorized Person
54	4550		1,066 KB	Unauthorized Person
55	4389		175 KB	Authorized Person
56	4575		294 KB	Authorized Person
57	4551		254 KB	Unauthorized Person
58	4577		570 KB	Authorized Person

				
59	4552		288 KB	Unauthorized Person
60	4553		3,308 KB	Unauthorized Person
61	4578		3,474 KB	Authorized Person
62	4554		3,375 KB	Unauthorized Person
63	4580		1,107 KB	Authorized Person
64	4581		170 KB	Authorized Person
65	4555		196 KB	Unauthorized Person
66	4556		1,224 KB	Unauthorized Person
67	4582		239 KB	Authorized Person

				
68	4557		244 KB	Unauthorized Person
69	4585		227 KB	Authorized Person
70	4559		291 KB	Unauthorized Person

CONCLUSION AND FUTURE ENHANCEMENT

5.1 CONCLUSION

In conclusion, a novel human identification method using a deep neural network for matching hand radiographs is presented in this project. The hand radiographs are an appropriate approach for human identification. A convolutional neural network (CNN) is an artificial intelligence algorithm that presents remarkable capabilities for forensic image analysis. Recently, there has been a great deal of interest in using this technology. CNN studies show a pre-processing, feature extraction and the training of the results. The use

REFERENCES

- 1) Sagar V.Joshi and Rajendra D. Kahphade, "Deep Learning Based Person Authentication Using Hand Radiographs: A Forensic Approach" in Proc. 2017 Preparation of Papers for IEEE Access, Februarym2017 doi: 10.1109 / ACCESS.2020.2995788.
- 2) X. Qu, T. Wei, C. Peng and P. Du, "A Fast Face Recognition System Based on Deep Learning," in Proc. 2018 11th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 2018, pp. 289-292.
- 3) Jie Lin, Jian-Ping Li, Hui Lin and Ji Ming, "Robust person identification with face and iris by modified PUM method," in Proc. 2009 International Conference on Apperceiving Computing and Intelligence Analysis, Chengdu, China, 2009, pp. 321-324.
- 4) I. Awate and B. A. Dixit, "Palm Print Based Person Identification," in Proc. 2015 International Conference on Computing Communication Control and Automation, Pune, India, 2015, pp. 781-785.
- 5) R. G. M. M. Jayamaha, M. R. R. Senadheera, T. N. C. Gamage, K. D. P. B. Weerasekara, G. A. Dissanayaka and G. N. Kodagoda, "VoizLock - Human Voice Authentication System using Hidden Markov Model," in Proc. 2008 4th International Conference on Information and Automation for Sustainability, Colombo, Sri Lanka, 2008, pp. 330-335.
- 6) S. Shunmugam and R. K. Selvakumar, "Electronic transaction authentication — A survey on multimodal biometrics," in Proc. 2014 IEEE International Conference on Computational Intelligence and Computing Research, Coimbatore, India, 2014, pp. 1-4
- 7) A'K. Bhat, B. Kumar and A. Acharya, "Radiographic imaging of the wrist", Indian journal of plastic surgery: official publication of the Association of Plastic Surgeons of India, vol. 44, no. 2, pp. 186-196, May 2011.
- 8) J. A. Kauffman, C. H. Slump, H. B. Moens, "Matching hand radiographs", in Proc. Overview of the workshops ProRISC-SAFE, November 17-18, 2005, Veldhoven, the Netherlands 2005 Nov , pp. 629-633.