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Lung X-Ray Image Enhancement to Identify Pneumonia with CNN

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***Abstract*— Chest x-rays have various values of intensity and high contrast. Chest X-rays require a contrast stretching process so that the image can be analyzed and diagnosed correctly. Image contrast improvement can be based on the histogram value of the image intensity. Pneumonia can be diagnosed by taking chest X-rays. Diagnosis of Pneumonia based on chest x-rays can be done automatically by a computer. Computer-based Pneumonia diagnosis requires a reliable and accurate algorithm. A reliable and accurate algorithm, namely Convolutional Neural Network. This research aimed to prove whether the chest X-ray image that was performed by contrast improvement had a significant effect in diagnosing Pneumonia. The algorithm proposed in diagnosing Pneumonia is a Convolutional Neural Network. The CLAHE repaired chest X-ray image was trained with 8 CNN architectural models. The training results of the eight CNN architectural models respectively have a loss function value of 0.0057, 0.028, 0.0964, 0.0446, 0.0473, 0.0573, 0.0979, 0.1407. The results of diagnostic testing for Pneumonia in the eight CNN architectural models were 79.65%, 79.01%, 80.29%, 76.92%, 82.53%, 80.45%, 79.81%, 78.04%, respectively. The highest accuracy result when testing is 82.53% with the CNN 35 Layers architectural model, with a description of the input image is grayscale with a size of 224x224.**

Keywords—CNN, Pneumonia diagnosis, chest X-ray, CLAHE.

I. INTRODUCTION

Advanced technology has enabled Artificial Intelligence to process digital images in the medical field [1]–[3]. Digital images can be analyzed automatically with computer support and reliable algorithms [1]. Digital images in the medical field have various intensities and high contrast and require a contrast stretching process so that images can display relevant information [2]–[6]. Information from medical images often has flaws and limitations, ranging from being unable to distinguish between disease and normal. Medical images need to be analyzed in detail and completely using contrast enhancement [2]–[6].

High contrast can be stretched by image contrast enhancement [2]–[4], [6]. One way to fix an image that is too contrast is based on the histogram value of the image [2]. Several studies that diagnose diseases in the medical field and image improvement have improved the contrast accuracy value. For example, studies of breast cancer diagnosis are 90-91% accurate [1]. The accuracy of diagnostic eye disease studies is more than 99% [2]. Research segmentation of liver medical images has significantly increased its accuracy [3]. Research related to CBCT and CT images to assist in operative or postoperative information is very effective [4]–[6].

Research related to deep learning and computer-assisted medical imagery is growing [7]–[15]. Medical images have limited information that is not clear because of the varying intensity values and high contrast. Medical imagery requires an accurate and reliable algorithm, for example by proposing a deep learning algorithm or Convolution Neural Network to be used in diagnosis [7]–[15]. Pneumonia disease is an infection caused by bacteria or viruses or fungi in one or both lungs. How to diagnose Pneumonia by taking chest X-rays [10]. Chest x-rays can be analysed with the help of computers and reliable algorithms to diagnose Pneumonia [10]. Several studies stated that the CNN (Convolutional Neural Network) algorithm has a high degree of accuracy in diagnosing Pneumonia from chest X-rays [7]–[15].

From previous studies, we propose that the chest X-ray image enhancement of the contrast stretch is based on the histogram values of the images [2]–[4]. Furthermore, chest x-rays were diagnosed with Pneumonia by the Convolutional Neural Network method [7]–[15]. Purpose of the research We proved whether the chest X-ray image with contrast enhancement had a significant effect on the diagnosis of Pneumonia using the Convolutional Neural Network algorithm. The structure of the content of this article consists of an abstract, introduction, research methodology, results and discussion, and conclusions.

II. RESEARCH METHODHOLOGY

A. Related Work

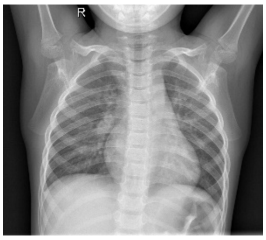
This research proposes a chest X-ray contrast enhancement based on the histogram value of the image [2]–[4]. The results of contrast enhancement chest X-rays were trained and diagnosed with Pneumonia using the Convolutional Neural Network algorithm [7]–[15].

B. Dataset

The image used in the research was taken from the Kaggle dataset [16]. Images that initially have a large and varied size are processed first. Table I shows the dataset used in this research. Table I images there are two types of Normal and Pneumonia. The processed image is converted to grayscale, then contrast correction is done with CLAHE. Fig. 1 shows a normal lung X-ray image of (a) original and (b) CLAHE-corrected results. Fig. 2 shows X-ray images of Pneumonia types that are (a) genuine and (b) the result of CLAHE repair.

TABLE I. DATASET

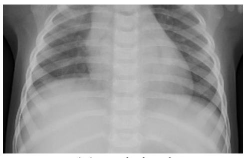
No	Type	Training	Testing	Total
1	Normal	1349	234	1583
2	Pneumonia	1930	390	2320
Total		3279	624	3903



(a) Original

(b) Result CLAHE

Fig. 1. Fig. 1. Normal Class Lung Ray Image



(a) Original

(b) Result CLAHE

Fig. 2. Pneumonia Class Lung Ray Image

C. Contrast Improvement of Chest X-rays

Chest X-rays have various intensity values and are too contrasting. An image that is too contrasting can be stretched the contrast. The stretch of contrast based on the value of the image histogram is called the Equalized Histogram or Adaptive Histogram Equalization (CLAHE). The process of equalization histogram or CLAHE is to produce an image with a uniform histogram value and sharpen the information from the image. The equalization histogram and CLAHE have different similarities, namely CLAHE divides the image into several blocks. The process of image improvement using the Adaptive Histogram Equalization is the same as the Equalization Histogram. Equation 1 is a way to do a new distribution of images based on the histogram value.

$$n(g) = max(0, round((L-1).\frac{c(g)}{N}) - 1) \qquad (1)$$

$n(g)$ is the new image intensity value, L is the maximum grayscale value, $c(g)$ the cumulative value of the total image intensity? N the total image size, for example, the image size is 8x8, then N is 64, and g is the image intensity value. Fig. 1 illustrates an illustration of the equalization histogram process. Fig. 3 (a) is an input image measuring 8x8, repairing the Equalization Histogram is done in Fig. 3 (b) and the results are in Fig. 3 (c). Fig. 3 (a) if illustrated is a grayscale input image that has a size of 8x8, and the intensity value is as in Table II. Table III explains each grayscale image intensity value from Table II, the appearance value of h(g) is calculated. Column g is the value of the intensity of the image or image-level 8 (0-7), (g) is the value of the occurrence of each level, and c(g) the cumulative value of the occurrence of the image level. Table IV is the image of the CLAHE improvement. Column n(g) in Table III is a new value from the image level in Table II, then this value is used as a reference to change the value of the image level. Suppose that the value for image-level 1 is replaced by 0, the value for image-level 2 becomes 0, and the value for image-level 3 is replaced by 2 as in Table IV.

0	1	2	3	3	3	1	0
4	4	2	3	3	3	4	4
4	4	2	3	3	3	4	4
4	4	2	3	3	3	4	4
4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6
6	7	7	7	7	7	7	6

(a) Original Image

g	h(g)	c(g)	n(g)
0	2	2	0
1	2	4	0
2	4	8	0
3	12	20	2
4	20	40	4
5	8	48	6
6	10	58	6
7	6	64	7
	64		

(b) Process Histogram Equalization

0	0	0	2	2	2	0	0
4	4	0	2	2	2	4	4
4	4	0	2	2	2	4	4
4	4	0	2	2	2	4	4
4	4	4	4	4	4	4	4
6	6	6	6	6	6	6	6
6	6	6	6	6	6	6	6
6	7	7	7	7	7	7	6

(c) Result Histogram Equalization

Fig. 3. Process of Equalization Histogram Repair

TABLE II. GRAYSCALE IMAGE INTENSITY VALUE

0	1	2	3	3	3	1	0
4	4	2	3	3	3	4	4
4	4	2	3	3	3	4	4
4	4	2	3	3	3	4	4
4	4	4	4	4	4	4	4
5	5	5	5	5	5	5	5
6	6	6	6	6	6	6	6
6	7	7	7	7	7	7	6

TABLE III. PROCESS HISTOGRAM EQUALIZATION

g	h(g)	c(g)	n(g)
0	2	2	0
1	2	4	0
2	4	8	0
3	12	20	2
4	20	40	4
5	8	48	6
6	10	58	6
7	6	64	7
	64		

TABLE IV. RESULT HISTOGRAM EQUALIZATION

0	0	0	2	2	2	0	0
4	4	0	2	2	2	4	4
4	4	0	2	2	2	4	4
4	4	0	2	2	2	4	4
4	4	4	4	4	4	4	4
6	6	6	6	6	6	6	6
6	6	6	6	6	6	6	6
6	7	7	7	7	7	7	6

D. Convolutional Neural Network

Convolutional Neural Network is a development of the Artificial Neural Network algorithm. Convolutional Neural Networks also have an input layer, hidden layer, and output layer. The input layer in CNN is an image with the same size between rows and columns. The hidden layer is a hidden layer, including the convolution layer, the pooling layer, the connected layer, and the activation layer. The output layer is the final layer that shows the type or class of the case research. The convolution layer is a layer that extracts features from the image. Fig. 4 (a) shows an input image with a size of 10x10 multiplied by a 3x3 filter in Fig. 4 (b), so the same image size is 10x10 with different intensity values in Fig. 4 (c).

0	0	0	0	0	0	0	0	0	0	0	0
0	24	21	37	14	8	24	16	29	28	34	0
0	9	30	26	10	7	20	23	5	20	31	0
0	14	18	4	32	36	13	25	17	26	24	0
0	19	11	7	39	43	16	20	26	28	13	0
0	6	16	31	13	10	26	13	6	29	11	0
0	4	0	23	9	8	24	8	19	22	11	0
0	20	0	3	29	34	17	14	38	11	17	0
0	31	26	8	34	40	18	26	20	22	45	0
0	38	23	26	59	37	21	56	43	55	23	0
0	53	2	88	98	72	107	87	82	44	31	0
0	0	0	0	0	0	0	0	0	0	0	0

(a) Image Input (Size 10x10)

-1	-1	-1
1	1	1
-1	-1	-1

(b) Filter

6	17	6	16	9	-2	21	25	35	11
-38	-53	-60	-88	-90	-72	-76	-93	-102	-61
-37	-66	-69	-60	-54	-55	-55	-54	-56	-42
-24	-52	-57	-37	-32	-44	-38	-42	-46	-49
-12	-11	-29	-75	-90	-70	-68	-75	-73	-34
-38	-49	-60	-80	-88	-74	-63	-62	-60	-35
-41	-69	-68	-56	-53	-59	-46	-54	-73	-72
-24	-45	-72	-106	-105	-95	-125	-149	-100	-39
-51	-121	-148	-218	-252	-236	-220	-127	-123	-64
-6	56	80	136	160	152	156	59	36	-3

(c) Convolution Result (Features)

Fig. 4. Illustration of the Convolution Layer Process

Layer Pooling has the function of selecting the most prominent or most important features of the convolution layer results. The Pooling Layer can apply the maximum value or the average value of the image intensity value in each kernel. The resulting convolution layer image is then taken with the most prominent features based on the maximum or average value of each 2x2 kernel. The initial image size is 10x10 if max-pooling with a 2x2 kernel will produce a 5x5 image. In addition to using the maximum value of the image intensity in CNN, the pooling layer can also use the average value of the image intensity according to the kernel size.

This research proposes 8 CNN architectural models. Table V shows the 8 model architectures proposed in diagnosing Pneumonia. Each CNN model proposed in Table V has a size or number of nodes in each convolution layer and pooling layer. For example, the CNN model architecture numbers 5 and 7 in Table 5 both have 35 layers, but the size and number of nodes in the convolution layer and the pooling layer are different. Fig. 5 shows the layer architectural arrangement of the CNN model.

Fig. 5 shows that the first layer is the input layer with the input image is [224 224 1]. 224x224 and grayscale image size. Fig. 5 explains that each convolution layer has a different number of nodes or filters, for example, in Fig. 5 the convolution layer has 32 nodes with a filter size of 3x3. Fig. 5 also explains that the size of the pooling layer, for example, has a node that is different from other pooling layers, but they both have a filter size of 2x2. The result of the pooling layer will change the image which was originally 224x224 in size after the pooling layer is done to 112x112. Fig. 6 describes in detail the proposed research. Fig. 6: X-rays of the lungs are processed first, equalizing the size to 224x224, and converted to grayscale. The input image of grayscale lung X-ray was 224x224 and corrected with CLAHE. Then the CNN training is carried out, the results of CNN training are the weights or models used for trials.

TABLE V. ARCHITECTURE MODEL CNN

No	Architecture Number of the Layer
1	15 Layers
2	19 Layers
3	27 Layers
4	23 Layers
5	35 Layers
6	31 Layers
7	35 Layers
8	31 Layers

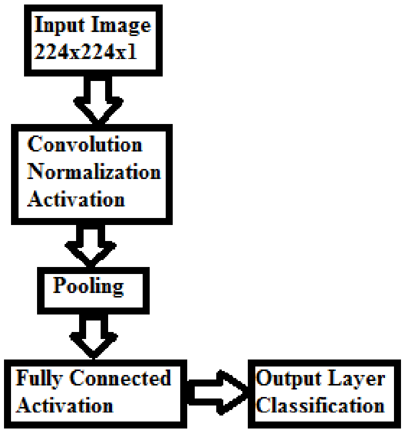


Fig. 5. The CNN Model Architectural

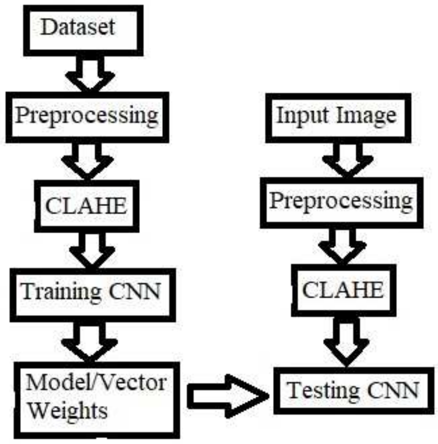


Fig. 6. Proposed Research

III. RESULT AND DISCUSSION

This research proposes a process of chest X-ray image enhancement with CLAHE based on previous studies related to contrast improvement in medical images [2]–[6]. The aim is to improve the chest X-ray image so that it can be used to diagnose Pneumonia with maximum and effective results. The algorithm used to diagnose Pneumonia is CNN [7]–[15]. The proposed algorithm is CNN with 8 different architectural models. The input layer of this case research is a grayscale image with a size of 224x224x1.

A. CNN Model 15 Layers

The first model has 15 layers consisting of several layers. Descriptions of the 15 layers are in Fig. 7. Fig. 7 shows the final image will be 56x56 in size. Fig. 7 illustrates that the convolution layer repeats three times, with the number of nodes, respectively, 32, 32, and 64.

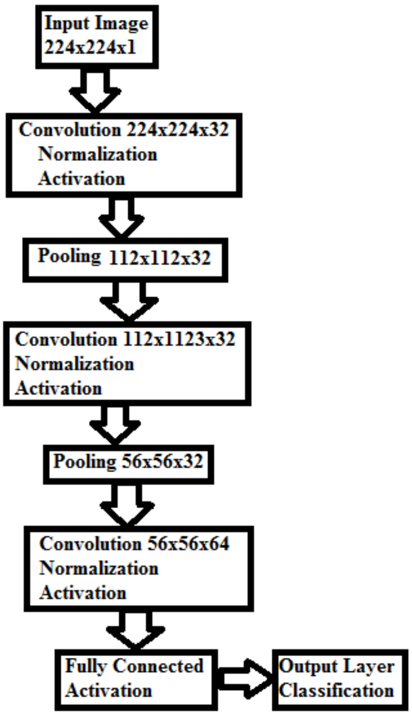


Fig. 7. CNN 15 Layers Architecture

B. CNN Model 19 Layers

The second model has 19 layers consisting of several layers. Descriptions of the 19 layers are in Fig. 8. Fig. 8 shows the final image will be 28x28 in size. Fig. 8 shows the convolution layer repeated four times, with the number of nodes, respectively, 32, 32, 64, and 64. The pooling layer uses the maximum function and repeats three times.

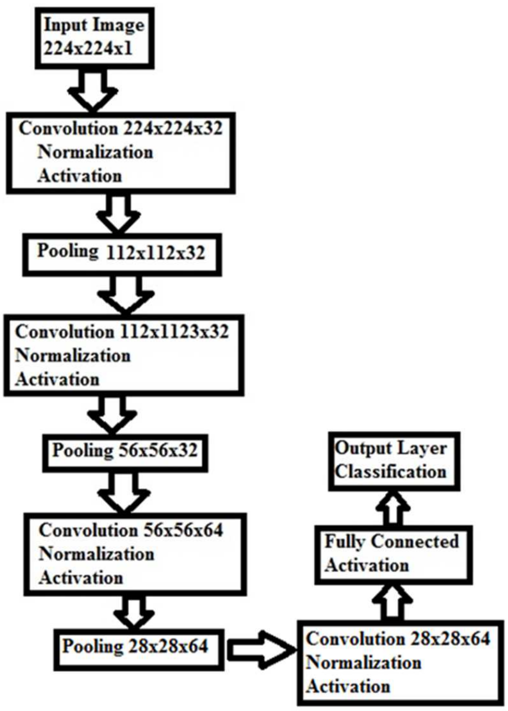


Fig. 8. CNN 19 Layers Architecture

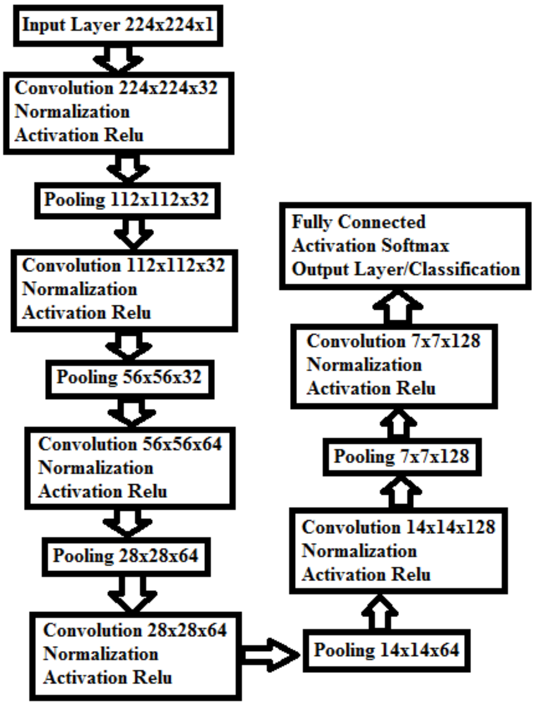


Fig. 9. CNN 27 Layers Architecture

C. CNN Model 27 Layers

The third model has 27 layers consisting of several layers. Descriptions of the 27 layers are in Fig. 9. Fig. 9 shows the final image will be 7x7 in size. Fig. 9 shows that there are six convolution layers, with the number of nodes, respectively 32, 32, 64, 64, 128, and 128. The pooling layer is repeated five times with maximum function.

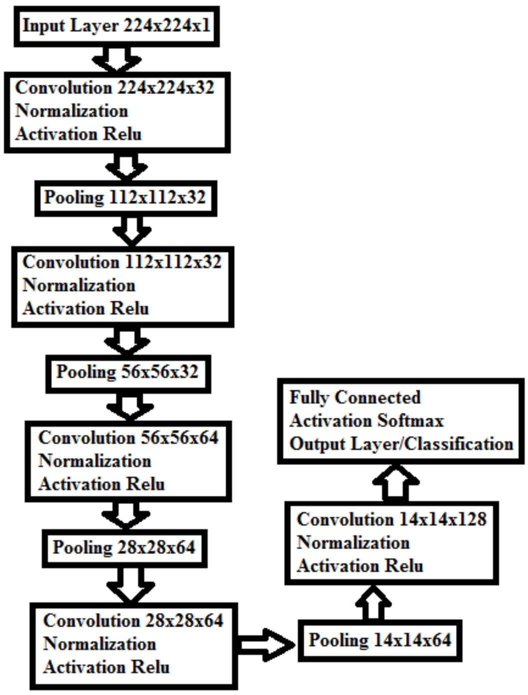


Fig. 10. CNN 23 Layers Architecture

D. *CNN Model 23 Layers*

The fourth model contains 23 layers consisting of several layers. Descriptions of 23 layers are in Fig. 10. Fig. 10 shows the result of the image to be 14x14 in size. Fig. 10 explains the convolution layer there are five times, with the number of nodes 32, 32, 64, 64, and 128, respectively. Fig. 10 pooling layer repeats four times with maximum function.

E. *CNN Model 35 Layers*

The fifth model has 35 layers consisting of several layers. Descriptions of the 35 layers are in Fig. 11. Fig. 11 shows the final image will be 1x1 in size. Fig. 11 shows that there are eight convolution layers, with the number of nodes, respectively 32, 32, 64, 64, 128, 128, 256, and 256. Fig. 11 pooling layer repeats itself seven times with maximum function.

F. *CNN Model 31 Layers*

The sixth model has 31 layers consisting of several layers. Descriptions of the 31 layers are in Fig. 12. Fig. 12 shows the final image will be 3x3 size. Fig. 12 shows that the convolution layer has seven times, with the number of nodes, respectively, 32, 32, 64, 64, 128, 128, and 256. Fig. 12 pooling layer is repeated six times with maximum function. The seventh and eighth models are almost the same as the fifth and sixth. The difference between the seventh and fifth layers is the number of nodes in the convolution layer. The seventh model of the number of nodes of the convolution layer is 16, 16, 32, 32, 64, 64, 128, 128, respectively. The seventh model for the input layer of the image is a grayscale image with a size of 224x224, and the final image will be 1x1 in size. The eight model nodes of the convolution layer are 16, 16, 32, 32, 64, 64, 128, respectively. The eight-model input layer of the image is a grayscale image with a size of 224x224, and the final image will be 3x3 in size.

Overall, the first to eight models show the input layer of the image is a grayscale image with a size of 224x224. Table VI describes the results of the accuracy of the trials for each of the proposed models. The seven models proposed with the highest accuracy value were 82.53%, namely the fifth model with 35 layers. The model proposed in Liang's research was to classify pneumonia in children with 96.7% accuracy [7]. Chhikara's deep CNN transfer learning model for diagnosing pneumonia is 90.1% accurate [9].

IV. CONCLUSION

This research proposes a process to improve chest X-ray images using CLAHE, the goal is to produce clear chest X-rays that can be used in diagnosing Pneumonia. The process of diagnosing Pneumonia uses the CNN algorithm by proposing 8 architectural models. Of the eight CNN architectural models with the highest accuracy value is the model with a total of 35 layers, with an accuracy of 82.53%.

TABLE VI. THE RESULTS OF THE MODEL EXPERIMENT ACCURACY

No	Number of Model Layers	Accuracy	Loss Function
1	15 layers	79.65%	0.0057
2	19 layers	79.01%	0.028
3	27 layers	80.29%	0.0964
4	23 layers	79.92%	0.0446
5	35 layers	82.53%	0.0473
6	31 layers	80.45%	0.0573
7	35 layers	79.81%	0.0979
8	31 layers	78.04%	0.1407

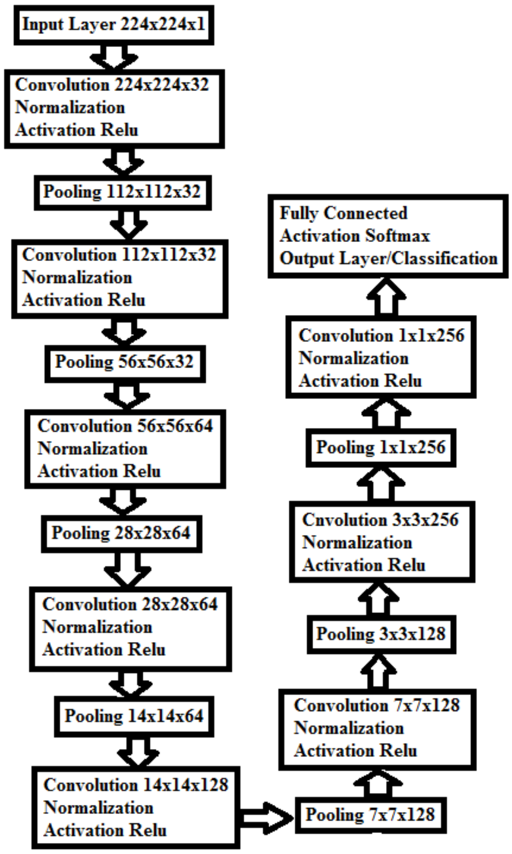


Fig. 11. CNN 35 Layers Architecture

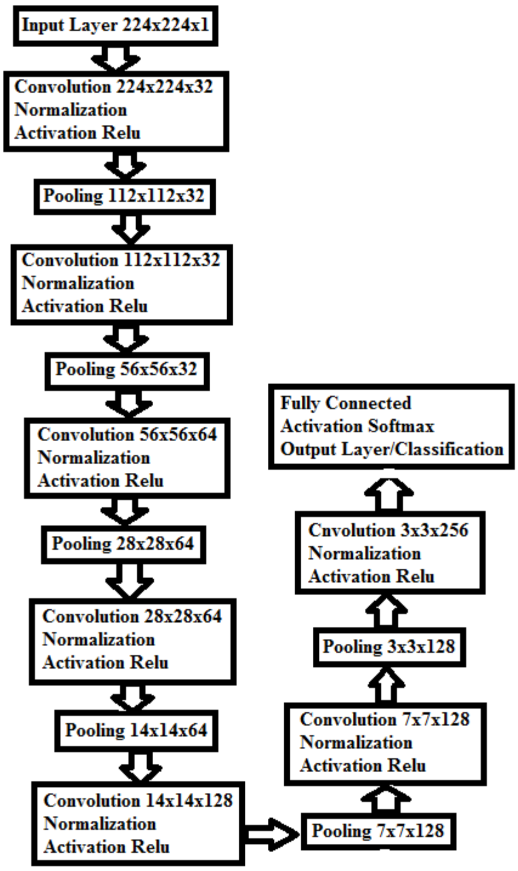


Fig. 12. CNN 31 Layers Architecture

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