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The Melanoma Skin Cancer Detection Using Convolutional Neural Network

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ABSTRACT

The most common cause of death for persons in the modern world is melanoma skin cancer. Melanoma is an aggressive kind of skin cancer that typically develops on parts of the body exposed to sunlight, UV radiation, dust, pollution, and microbes. A study found that 79% of humans who do have melanoma skin cancer in its early stages are unaware of having it. When it is finally identified, it may have progressed further into the skin and may have impacted other parts of the body, making treatment extremely difficult and it also makes the survival rate for humans very low. As a result, melanoma skin cancer kills the majority of its victims. If melanoma is identified or recognized in the early stages, then it could have been cured easily and it also has a bigger survival rate for humans. There is an automated system that has been designed with the compilation of data sets with a variety of diagnoses. This automated system will help to detect in early stages of melanoma. Convolutional neural network technology was initially employed in our automated system to classify data. But as a result, our accuracy was poor. Then, we used support vector machines (SVMs) to analyze the entire dataset after categorizing and segmenting the data into zones, using Tensor Flow libraries to implement the entire model. After using the model, we achieve a 96% accuracy rate.

Keywords:-*Melanoma, Skin cancer , Detection, Convolutional Neural Network , Tensor Flow, Support Vector Machine(SVM), Image Processing , Machine Learning.*

INTRODUCTION

The skin protects the body from harm, diseases, heat, and sunlight. Skin also retains water and fat which helps in maintaining body temperature. The epidermis and dermis are the two major layers of the human skin [1].

The epidermis, or top layer of skin, is made up of three different cell types: BASAL cells, which give skin its round shape, SQUAMOUS cells, which are flat and scaly on the surface, and melanocytes, which give skin its color and shield it from harm [7].

The skin cancer is one of the major diseases. Which can be prevented if it is being detected in early stages. But the majority of skin cancer can't get detected early because of the lack of knowledge.

People don't notice skin cancer at early stages. Which leads the cancer to be spread across the human body and gets very difficult to cure or prevent. It also decreases the survival rate among people which causes deaths among people [10].

There are two types of skin cancer: malignant melanoma and non-melanoma. There are four types of melanoma skin cancer [7]. They are-

Superficial Spreading Melanoma
The kind of melanoma that spreads superficially is the most common. It often appears like black pigment growing out from a mole. It usually occurs on skin that has been exposed to a lot of UV radiation, either natural or artificial [7].

Nodular Malignant Melanoma
Nodular melanoma is the outward sign of Pink, red, brown, or black hard bumps are the outward that is pink, red, brown or black. It could form a crusty, readily bleed able surface. Typically, the head and neck are affected [7].

Lentigo malignant Melanoma
The malignant melanoma that causes lentigo has the slowest rate of growth. Usually on the cheeks, ears, or arms, it appears as a black stain with an irregular border. It has no connection to a mole [7].

Acral Lentiginous Melanoma
Acral lentiginous melanoma may manifest as a bruise-like spot, a colorless or light-colored region, or both. It typically appears under the nails, on the palms or soles of the hands or feet. Asians and those with darker complexion, such as those of African heritage, are more likely to develop this kind of melanoma than fair-skinned individuals [7].

The epithelial layer or outer surface of the skin that has developed malignantly is referred to as non-melanoma skin cancer [8]. Non melanoma skin cancer always responds to therapy and hardly expands to other skin tissues. Malignant Melanoma skin cancer is also known as Melanoma skin cancer. One of the most dangerous and deadly forms of cancer is malignant melanoma. According to study, it has shown that only 4% of the population is determined to be affected and this causes 75% of melanoma skin cancer deaths [1].

Nearly 55,000 people every year acquire this kind of cancer [2]. Melanoma is a rather prevalent kind of cancer compared to other cancers. The reasons behind increasing melanoma skin cancer are - sunlight, UV radiation, dust, pollution, and microbes. Melanoma occurs as an effect of having an abundance of melanocytes, which are found throughout the body. There are many reasons behind this cancer. But the major cause of spreading melanoma skin cancer is people's ignorance [1].

When it comes to early stages, people don’t take it seriously. As a result, when it comes to the final stage it does not fully reflect the diversity of the condition, and it is not possible to accurately predict how it will progress or to treat it.

In addition, cancer cells are frequently discovered and treated until they have spread to other internal parts of the body and undergone mutations [3]. Therapies and treatments are not particularly efficient at that time.

Because of this kind of ignorance, many people are dying day by day. Melanoma should never be taken lightly, but treating a melanoma as soon as it appears rather than waiting for it to spread might save a life [3].

So, the author has designed an automated system so that people can detect this skin cancer easily in the early stage and recover it as soon as possible by taking proper treatment.

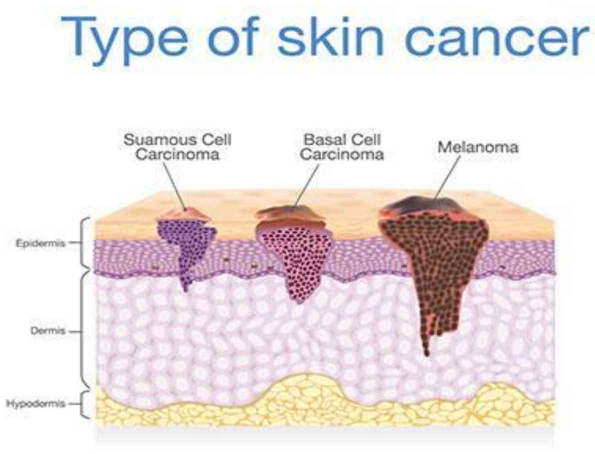


Fig.1:-*Phases of skin cancer melanoma.*

Research Motivations and Objectives

Melanoma Skin cancer is becoming one of the major diseases in the human body. Melanoma has a better survival rate at early stages. That means it can be treated very easily if it gets detected in an early stage. But the majority of people who have suffered from melanoma, could not detect it in an early stage which lead them to very complicated treatment and even also deaths. This is why, In this thesis, we would like to implement an automated system which can detect this cancer in an early stage and will also be easily accessible for people everywhere.

If people can detect this cancer in an early stage, the can easily treat themselves for their betterment and they can avoid these deadliest circumstances if they get the proper treatment very early. This also increases the survival rate among humans. This is why the main objective of this thesis is to develop an automated system that can detect Melanoma Skin Cancer accurately.

LITERATURE REVIEW

The area of melanoma skin cancer detection has utilized a variety of approaches and algorithms over time. The author proposed an automated system using custom CNN method, SVM method and tensor flow libraries to detect the disease of Melanoma skin cancer. The authors have tried to address the same problem using those mentioning techniques.

The majority of previous articles concentrated on feature extraction before moving on to illness prediction. In Paper [5] CNN and SVM for dealing with this complex problem and the authors used to classify skin cancer and made a comparison based on the performance of those classifiers.

In publication [2,4], the authors put up a method for melanoma skin cancer detection and feature extraction using a variety of image processing techniques, including Otsu thresholding, which isolates the lesion from the total picture. Paper [1] is basically similar to paper [2,4] but the main difference is in paper [1] the author has proposed melanoma skin detection using image processing techniques and machine learning. In paper [3], the author proposed a skin cancer detection system using Thresholding, SVM, GLCM, Skin cancer, Classifier for early detection of skin cancer disease. In paper [6], the author proposed an automated system to detect skin cancer using deep learning to select and categorize the best available approaches to skin cancer detection using neural networks (NNs) and also to collect and analyze existing studies according to predefined evaluation criteria. In paper [7], the author proposed an algorithm for diagnosing malignant melanoma skin cancer.

In this paper, the author separates skin lesions in color images to extract color features, and gray level images to extract texture features. In paper [8], the author has used segmentation, feature extraction and abcd rule for detecting melanoma skin cancer. The author has used data segmentation which is the process of grouping your data into at least two subsets, although more separations may be necessary on a large network with sensitive data. There are also many authors who have proposed the same proposal with some lower accuracy rate among the file.

METHODOLOGY

For collecting the accurate resources, some tools/data resources have been used. Tools like Google Scholar, IEEE Xplore, Research Gate, ACM, IGI Global have been used to collect accurate resources. There were less resources based on the desired topic. The resources have been picked very carefully. By following the resources, some clear instructions could be found to implement the automated system for detecting melanoma skin cancer.

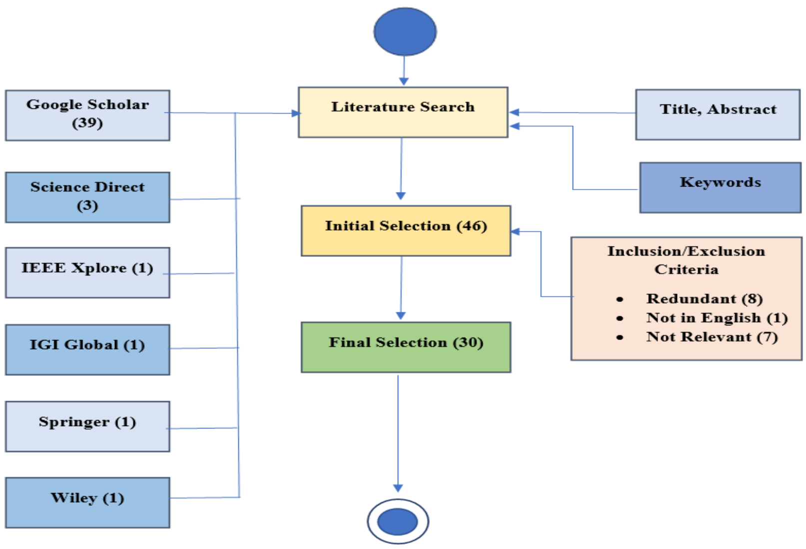


Fig.2

This model has been designed in some phases. In early phases, the model is involved in collecting the required datasets.

This phase also involves pre-processing the images which leads to detecting certain parameters of the images collected from the datasets. In the next phases, the collected images are being classified based on its specification and measurements.

PRE-PROCESSING

In this stage the datasets have been collected and the selected images have been specified by its specification during this stage. This also includes specifying images by its measurements and specification also collecting images from the given dataset.

DATASET

Here the dataset which has been used in the project is called Skin Cancer MNIST:

HAM10000 (https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000) which has been found on kaggle.com. Originally it is an ISIC dataset which is also used by Harvard Data verse. Those major problems almost have been after the release of the HAM10000 ("Human against Machine with 10000 training images") dataset. There are many dermatoscopic images collected from different populations, acquired and have been stored by different modalities.

CLASSIFICATION

Here in this paper, classification plays an important role. Here the selected images have been classified by their measurements which can help this system to reach a good level of accuracy. In this paper, the data have been classified from the selected images from the dataset and the classified datasets have been used to train the model. In this paper we have used 6 classes based on data specifications. This will improvise our accuracy rate after getting trained by the data.

MODEL SELECTION

In this paper several models have been used to implement the automated system. There are 3 different models that have been used to design the automated system. Custom Convolutional Neural Networks, Tensor flow and Support Vector Machine have been used to design and train this system. In this paper, the Custom CNN model was implemented twice. At first, the model was not that robust, the datasets were not properly measured and that made the accuracy rate lower. Later this model has been improved by classifying the data, adding more layers, splitting the images, a larger kernel size has been used, ReLU functions and softmax functions also have been used to improve the accuracy rate of that model and also to make the model more robust. A model can be called a robust model if its output or forecasts are consistently accurate even if some variables are drastically changed due to some circumstances. In this system, tensor flow has been used to add more layers in data that can be trained to predict a better result. SVM has been used to classify the data. For implementing the system with higher accuracy, flattering the data also has been used to convert the data from multi-dimensional array to single-dimensional array which gives a better training for those data and improves the accuracy rate. These factors lead to a good accuracy rate for this model.

```
] # reference: https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000/discussion/183083
  classes={
      0:('akiec', 'actinic keratoses and intraepithelial carcinomae'),

      1:('bcc' , 'basal cell carcinoma'),

      2:('bkl', 'benign keratosis-like lesions'),

      3:('df', 'dermatofibroma'),

      4:('nv', ' melanocytic nevi'),

      5:('vasc', ' pyogenic granulomas and hemorrhage'),

      6:('mel', 'melanoma'),
  }
```

Fig.3:*-The declaration of classes*

```
model = Sequential()

model.add(Conv2D(16,
                 kernel_size = (3,3),
                 input_shape = (28, 28, 3),
                 activation = 'relu',
                 padding = 'same'))

model.add(MaxPool2D(pool_size = (2,2)))
model.add(tf.keras.layers.BatchNormalization())

model.add(Conv2D(32,
                 kernel_size = (3,3),
                 activation = 'relu'))

model.add(Conv2D(64,
                 kernel_size = (3,3),
                 activation = 'relu'))

model.add(MaxPool2D(pool_size = (2,2)))

model.add(tf.keras.layers.BatchNormalization())

model.add(Conv2D(128,
                 kernel_size = (3,3),
                 activation = 'relu'))

model.add(Conv2D(256,
                 kernel_size = (3,3),
                 activation = 'relu'))

model.add(Flatten())
model.add(tf.keras.layers.Dropout(0.2))
model.add(Dense(256,activation='relu'))

model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.Dropout(0.2))
```

```
model.add(Flatten())
model.add(tf.keras.layers.Dropout(0.2))
model.add(Dense(256,activation='relu'))

model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.Dropout(0.2))
model.add(Dense(128,activation='relu'))

model.add(tf.keras.layers.BatchNormalization())
model.add(Dense(64,activation='relu'))

model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.Dropout(0.2))
model.add(Dense(32,activation='relu'))

model.add(tf.keras.layers.BatchNormalization())
model.add(Dense(7,activation='softmax'))

model.summary()
```

Fig.4:-*The Data Layer*

```
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d (Conv2D)             (None, 28, 28, 16)        448

max_pooling2d (MaxPooling2D  (None, 14, 14, 16)       0
)

batch_normalization (BatchN  (None, 14, 14, 16)       64
ormalization)

conv2d_1 (Conv2D)           (None, 12, 12, 32)        4640

conv2d_2 (Conv2D)           (None, 10, 10, 64)        18496

max_pooling2d_1 (MaxPooling  (None, 5, 5, 64)         0
2D)

batch_normalization_1 (Batc  (None, 5, 5, 64)         256
hNormalization)

conv2d_3 (Conv2D)           (None, 3, 3, 128)         73856

conv2d_4 (Conv2D)           (None, 1, 1, 256)         295168

flatten (Flatten)           (None, 256)               0

dropout (Dropout)           (None, 256)               0

dense (Dense)               (None, 256)               65792

batch_normalization_2 (Batc  (None, 256)              1024
hNormalization)

dropout_1 (Dropout)         (None, 256)               0

dense_1 (Dense)             (None, 128)               32896

=================================================================
Total params: 504,103
Trainable params: 502,983
Non-trainable params: 1,120
_________________________________________________________________
```

Fig.5:-*The model summary*

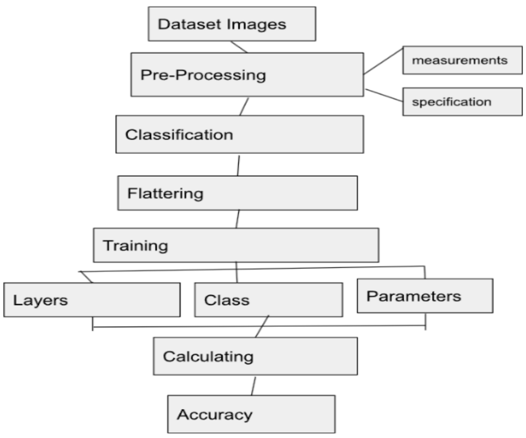


Fig.6:-*Implementation Block Diagram.*

RESULTS & ANALYSIS

This system has been implemented twice for better accuracy. After the first implementation, the main accuracy rate was at 72%. Which is not that higher for a medical condition. Using dermatological images with different measurements without making a robust Custom CNN and the lack of resources and good dataset, it was quite difficult to implement this system with higher accuracy.

	precision	recall	f1-score	support
akiec	0.33	0.19	0.24	37
bcc	0.53	0.51	0.52	55
bkl	0.51	0.36	0.42	113
df	0.50	0.33	0.40	12
nv	0.85	0.87	0.86	669
vasc	0.80	0.40	0.53	10
mel	0.40	0.58	0.47	106
accuracy			0.72	1002
macro avg	0.56	0.46	0.49	1002
weighted avg	0.72	0.72	0.72	1002

Fig.7:-*The accuracy rate of the first Implementation.*

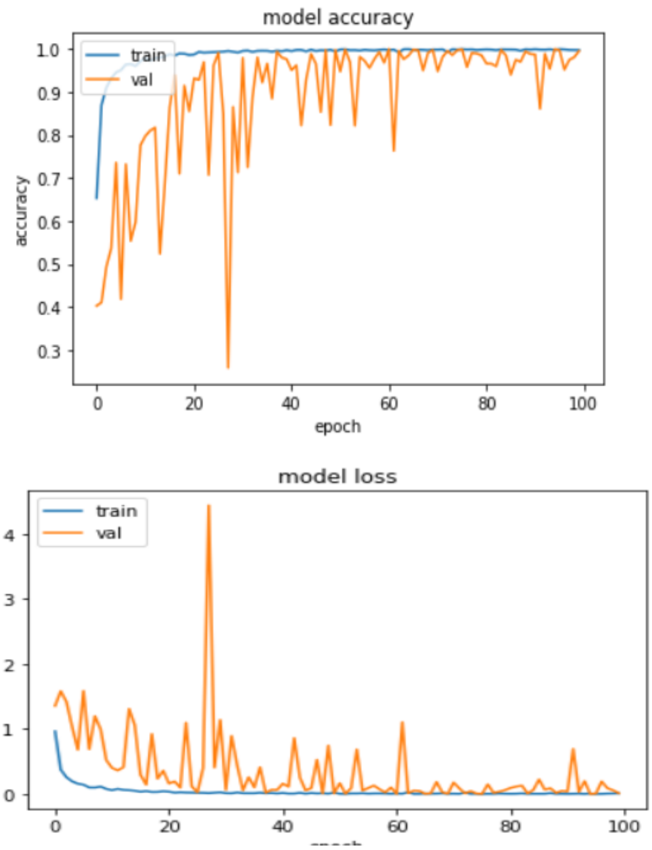


Fig.8:-*The Model accuracy and the Model loss curve of the first Implementation.*

There were really few datasets and very few resources for implementing this system. This is why classifying the datasets and improvising the model was a better solution to improve the accuracy rate of this system. The datasets have been classified by its specification, measurements and class. After that, flattering the data was important to train the model. After that a convolutional base has been created. After that there were many layers which were added through TensorFlow. In the layers, ReLU functions were activated. The Dense layer has been added to classify images based on output from convolutional layers. After that, the classes which help to classify the data. After implementing the system with this model, the model was able to detect the data and was giving such a higher accuracy. This model has given almost 96% accuracy based on classified dataset and a robust Custom CNN model.

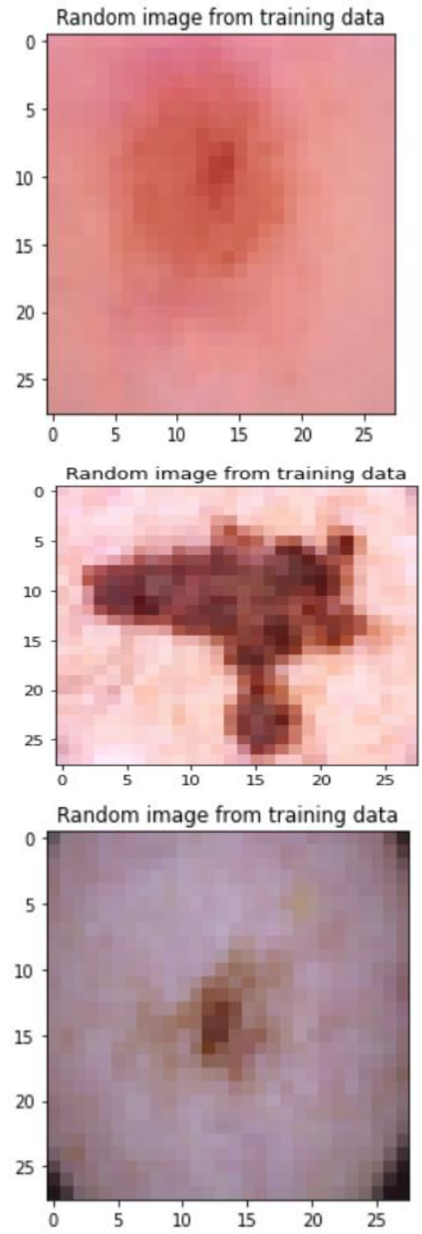
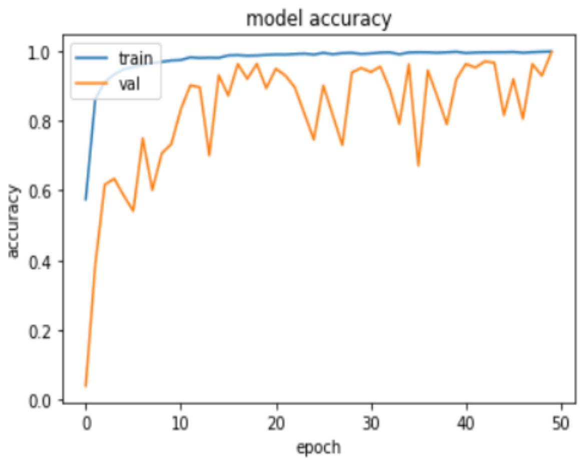


Fig.9:-*Random Input Images of final implementation .*

These input images have been taken randomly from the classified dataset. Which was used to train this model of this project. After giving random images to the implemented system the system does all the necessary calculations and we can see the outcomes through the Model Accuracy and Model Loss curve.

```
#plot of accuracy vs epoch

plt.plot(history.history['accuracy'])

plt.plot(history.history['val_accuracy'])

plt.title('model accuracy')

plt.ylabel('accuracy')

plt.xlabel('epoch')

plt.legend(['train', 'val'], loc='upper left')

plt.show()
```




```
#plot of loss vs epoch

plt.plot(history.history['loss'])

plt.plot(history.history['val_loss'])

plt.title('model loss')

plt.ylabel('loss')

plt.xlabel('epoch')

plt.legend(['train', 'val'], loc='upper left')

plt.show()
```

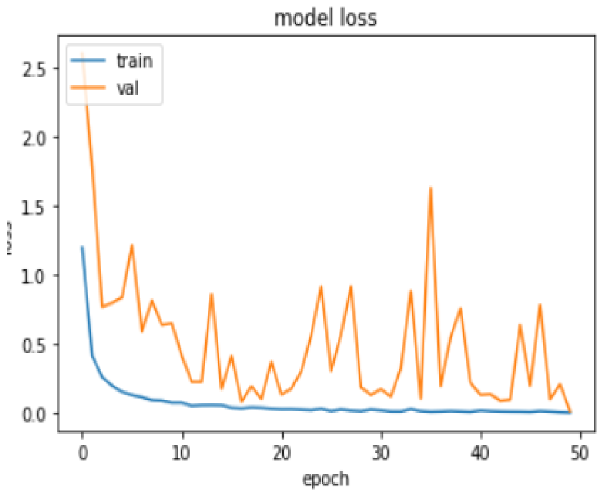


Fig.10:-*The model accuracy and model loss curve in the final implementation.*

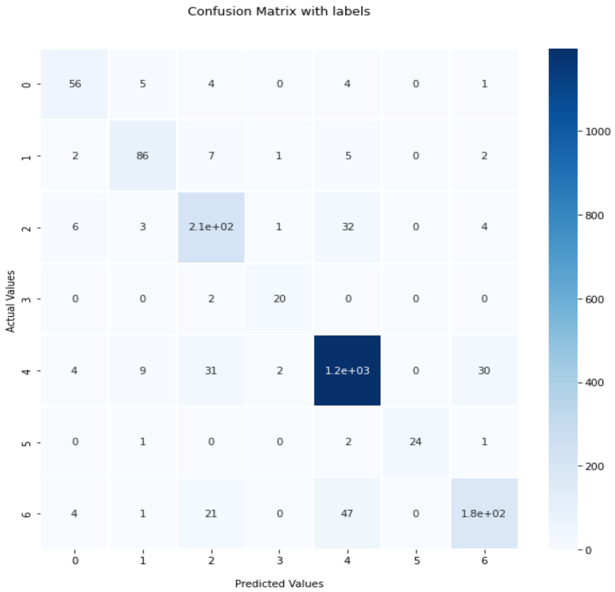


Fig.11:-*Confusion Matrix with labels for the final Implementation.*

After implementing everything, the automated system for detecting Melanoma Skin cancer is being completed with better accuracy. This model will help to detect this skin cancer in early stages which will make people more aware about this problem. And if it is being detected at an early stage, then this problem can be cured very easily.

	precision	recall	f1-score	support
akiec	0.97	0.95	0.96	73
bcc	0.88	0.98	0.93	98
bkl	0.90	0.93	0.92	223
df	0.94	0.80	0.86	20
nv	0.97	0.98	0.97	1345
vasc	0.97	1.00	0.98	28
mel	0.95	0.85	0.90	216
accuracy			0.96	2003
macro avg	0.94	0.93	0.93	2003
weighted avg	0.96	0.96	0.96	2003

Fig.12:-*The accuracy rate for the final implementation*

CONCLUSION

The aim of this system is to accurately detect Melanoma Skin cancer by processing its image. Melanoma skin cancer mainly affects human skin and spreads in inner human body parts through human skin. In early stages, this can easily be prevented. But in later stages, it's quite difficult to prevent, which leads to a lower survival rate for humans. This causes human deaths. This project can be used to detect this cancer in early stages with a better accuracy rate. This model is being developed so that this cancer can be detected and can be cured in early stages. This system gives a better accuracy which will give a better result to detect and prevent Melanoma Skin Cancer in early stages. Which will give a better survival rate for humans as it will be detected in early stages. This will reduce the death rate of humans in Skin cancer if it is being detected in early stages.

REFERENCES

1. Vijayalakshmi (2019). M. M. Melanoma skin cancer detection using image processing and machine learning. *International Journal of Trend in Scientific Research and*
2. Gopinathan, S., & Rani, S. N. A. (2016). The melanoma skin cancer detection and feature extraction through image processing techniques. *orthopedics*, *5*(11), 2016..
3. [3] Ansari, Bano,U, Sarode T(2017). Skin cancer detection using image processing. *Int. Res. J. Eng. Technol* 4.4 (2017): 2875-2881.
4. Aima, A., & Sharma, A. K. (2019, February). Predictive approach for melanoma skin Cancer detection using CNN. In *Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur-India*..
5. Brindha, P. G., Rajalaxmi, R., Kabhilan, S., Sangitkumar, C., & Sanjeevan, L. (2020). Comparative study of SVM and CNN in identifying the types of skin cancer. *J. Crit. Rev*, *7*(11), 640-643.
6. Kaur, H., & Singh, A. (2015). A Review on Automatic Diagnosis of Skin Lesion Based on the ABCD Rule & Thresholding Method. *International Journal of Advanced Research in Computer Science and Software Engineering Research Paper*, *5*(5), 326-331.
7. Jain, S., & Pise, N. (2015). Computer aided melanoma skin cancer detection using image processing. *Procedia Computer Science*, *48*, 735-740.
8. Ramteke, N. S., & Jain, S. V. (2013). ABCD rule based automatic computer-aided skin cancer detection using MATLAB. *International Journal of Computer Technology and Applications*, *4*(4), 691.
9. Bhardwaj, A., & Bhatia, J. S. (2014). An image segmentation method for early detection and analysis of melanoma. *IOSR Journal of Dental and Medical Sciences*, *13*(10), 18-22.
10. Bono, A., Tomatis, S., Bartoli, C., Tragni, G., Radaelli, G., Maurichi, A., & Marchesini, R. (1999). The ABCD system of melanoma detection: A spectrophotometric analysis of the asymmetry, border, color, and dimension. *Cancer: Interdisciplinary International Journal of the American Cancer Society*, *85*(1), 72-77.
11. Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., ... & Mahnashi, M. H. (2021). Skin cancer detection: a review using deep learning techniques. *International journal of environmental research and public health*, *18*(10), 5479.