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**PROJECT PROPOSAL**

**Department of Electronics and Computer Engineering**

**Topic:** Melanoma Detection Using Deep Learning (DL).

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**Introduction**

Skin cancer is a dangerous and widespread disease. Each year there are approximately 5.4 million new cases of skin cancer recorded in the USA alone. The global statistics are equally alarming. Recent reports show that the incidence of melanoma has risen considerably over the past 30 years, and more than 96,000 new cases are estimated to be diagnosed in the United States in 2019 **{according to the recently published Cancer Facts & Figures 2019 report from the American Cancer Society}**. The mortality rate of this disease is expected to rise in the next decade. The survival rate is less than 14% if diagnosed in later stages. However, if skin cancer is detected at early stages, the survival rate is nearly 97%. This demands the early detection of skin cancer. This project will address the issue of early diagnosis with improved accuracy.[1]

Skin cancer is very common in Europe, Australia and USA [21] and is almost always curable if recognized and treated early. The major risk factors related are skin color, sun exposure, climate, advanced age, genetic and familial history. The best way to detect melanoma is to recognize a new spot in the skin or a spot that is changing in size, shape and color. Early detection of skin cancer can avoid death [22]

**What is Melanoma**

Melanoma is a form of skin cancer that begins in the cells (melanocytes) that control the pigment in your skin. This illustration shows melanoma cells extending from the surface of the skin into the deeper skin layers.

Melanoma is usually curable when detected and treated early. Once melanoma has spread deeper into the skin or other parts of the body, it becomes more difficult to treat and can be deadly. The estimated five-year survival rate for U.S.[2]

**Description of the problem being solved**

To diagnose skin cancer speedily at the earliest stage and solve some of the problems mentioned above, there have been extensive research solutions by developing computer image analysis algorithms. The majority of these algorithmic solutions were parametric, meaning that they required data to be normally distributed. As data cannot be controlled, these methods would be insufficient to diagnose the disease accurately. However, non-parametric solutions do not rely on the constraint that the data is in standard distribution form.



Figure: Melanoma Image [17][18]

In this work, we address the problem of skin cancer classification using convolutional neural networks. Many cancer cases early on are misdiagnosed, leading to severe consequences, including the patient’s death. Also, there are cases in which patients have other problems, and doctors interpret it as skin cancer. This leads to unnecessary time and money spent for further diagnosis. This work will solve both of the above problems using deep neural networks and ResNet50 architecture. We will use publicly available ISIC databases for both training and testing our network.

**Machine learning**

Machine learning (ML) is the study of computer algorithms that improve automatically through experience and by the use of data. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so.[3] Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.[3]

**Deep Learning**

Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.[4]

Deep learning can be considered as a subset of machine learning. It is a field that is based on learning and improving on its own by examining computer algorithms. While machine learning uses simpler concepts, deep learning works with artificial neural networks, which are designed to imitate how humans think and learn.[5] Until recently, neural networks were limited by computing power and thus were limited in complexity. However, advancements in Big Data analytics have permitted larger, sophisticated neural networks, allowing computers to observe, learn, and react to complex situations faster than humans.[5] Deep learning has aided image classification, language translation, speech recognition. It can be used to solve any pattern recognition problem and without human intervention.

**Convolutional Neural Networks(CNN)**

CNN’s are a kind of neural network that has proven to be very powerful in image recognition and classification. CNN’s can identify faces, pedestrians, traffic signs, and other objects better than humans and therefore are used in real-time applications like robots and self-driving cars.CNN’s are a supervised learning method and are trained using labeled data given with the respective classes. CNN’s learn the relationship between the input objects and the class labels and comprise two

components: the hidden layers in which the features are extracted and, at the end of the processing, the fully connected layers used for the actual classification task. The hidden layers of CNN have a specific architecture consisting of convolutional layers, pooling layers, and activation functions for switching the neurons either on or off. In a typical neural network, each layer is formed by a set of neurons, and one neuron of a layer is connected to each neuron of the preceding layer while

The architecture of hidden layers in CNN is slightly different. The neurons in a layer are not connected to all neurons of the preceding layer; instead, they are connected to only a small number of neurons from the previous layer. This restriction to local connections and additional pooling layers summarizing local neuron outputs into one value results in translation-invariant features. This results in a more straightforward training procedure due to fewer parameters and lower model complexity.

The Diagram as follows:

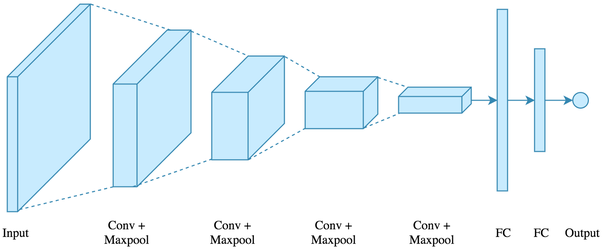


Figure: Layers Of CNN [6]

**Proposed Method**

We will use the concept of ResNet50 for classification. With ResNet50, instead of starting the learning process from scratch, the model starts from patterns that have been learned when solving a different problem. This way, the model leverages previous learnings and avoids starting from scratch. In image classification, ResNet50 is usually expressed through the use of pre-trained models. A pre-trained model is a model that was trained on a large benchmark dataset to solve a problem similar to the one that we want to solve.

Moreover, jupyter notebook will be used to build the model .

**ResNet50**

ResNet 50 architecture was re-trained on our dataset by fine-tuning across all layers and replacing top layers with one average pooling, one fully connected. Finally, the softmax layer allows the classification of 2 diagnostic categories. The input images’ size was all resized to (224, 224) to be compatible with this model. The learning rate was set to 0.0001 and Adam was used for the optimizer.[18] It uses identity mapping to map the inputs. This identity mapping does not have any parameters and is just there to add the output from the previous layer to the layer ahead. The identity mapping is multiplied by a linear projection to expand shortcuts’ channels to match the residual. The Skip Connections between layers add the outputs from previous layers to the outputs of stacked layers. This results in the ability to train much deeper networks than what was previously possible.

**Proposed Model**

This is the proposed model of the whole system using ResNet50

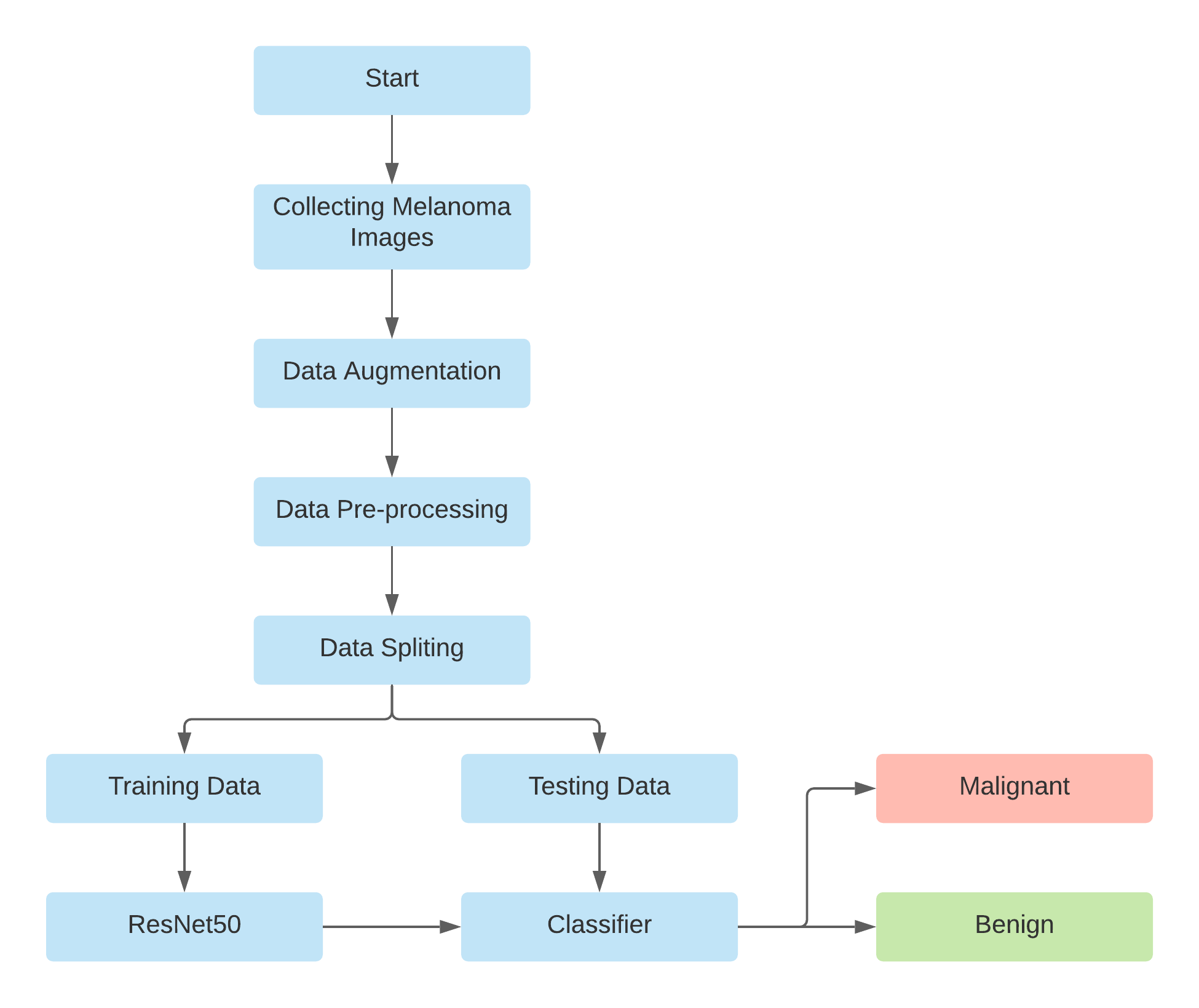


Figure: Proposed Model

**Proposed Solution**

After preprocessing data we will split the data into two portions. 70% will be used to train the model & 30% data will be used to test the model. After training the model the new data will be predicted in the trained model. Afterward the model gives the predicted result if the tumor is benign or malignant.

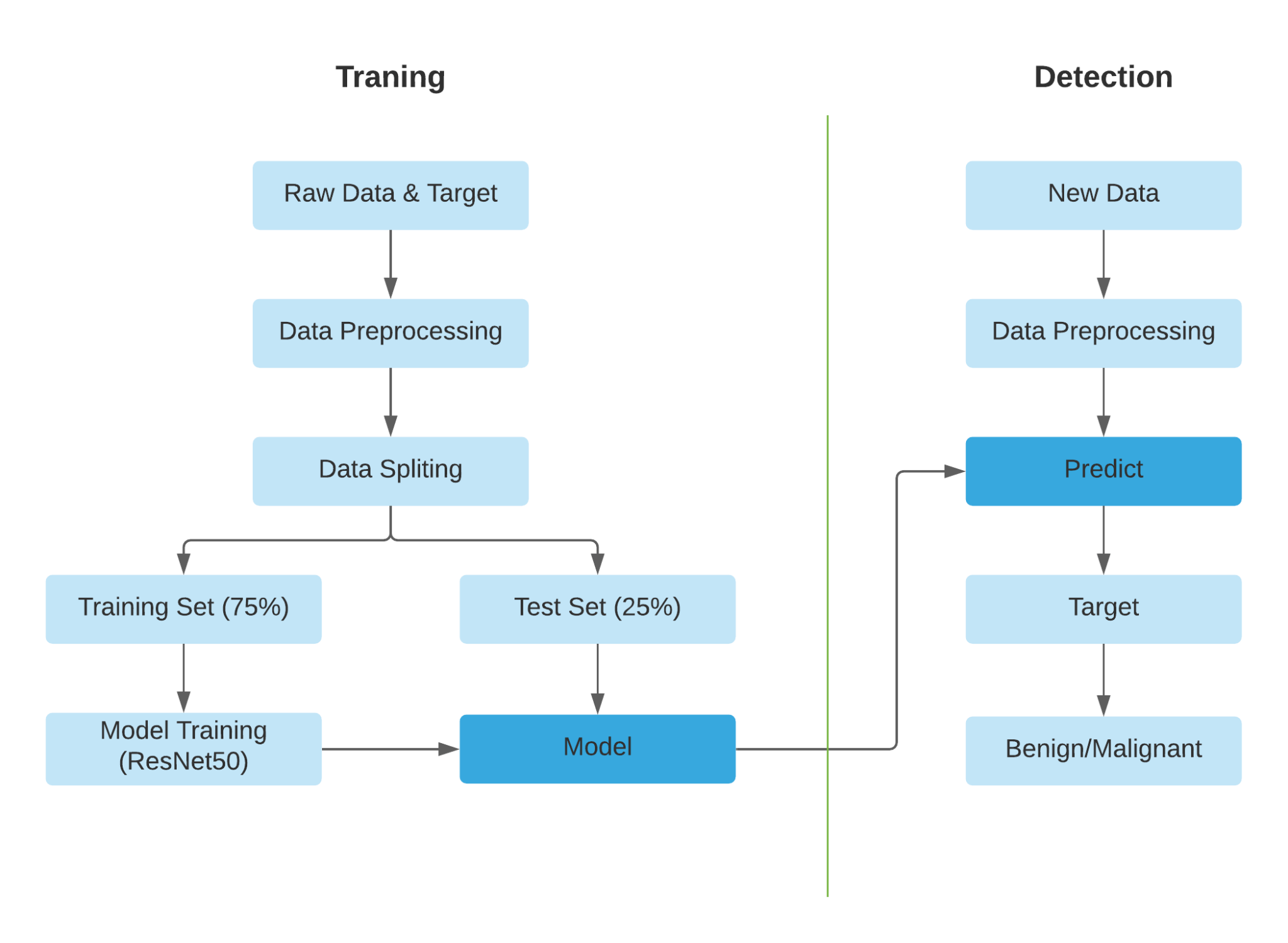
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Figure: Proposed Solution

**System Flowchart**

The system will work as follows to predict melanoma.

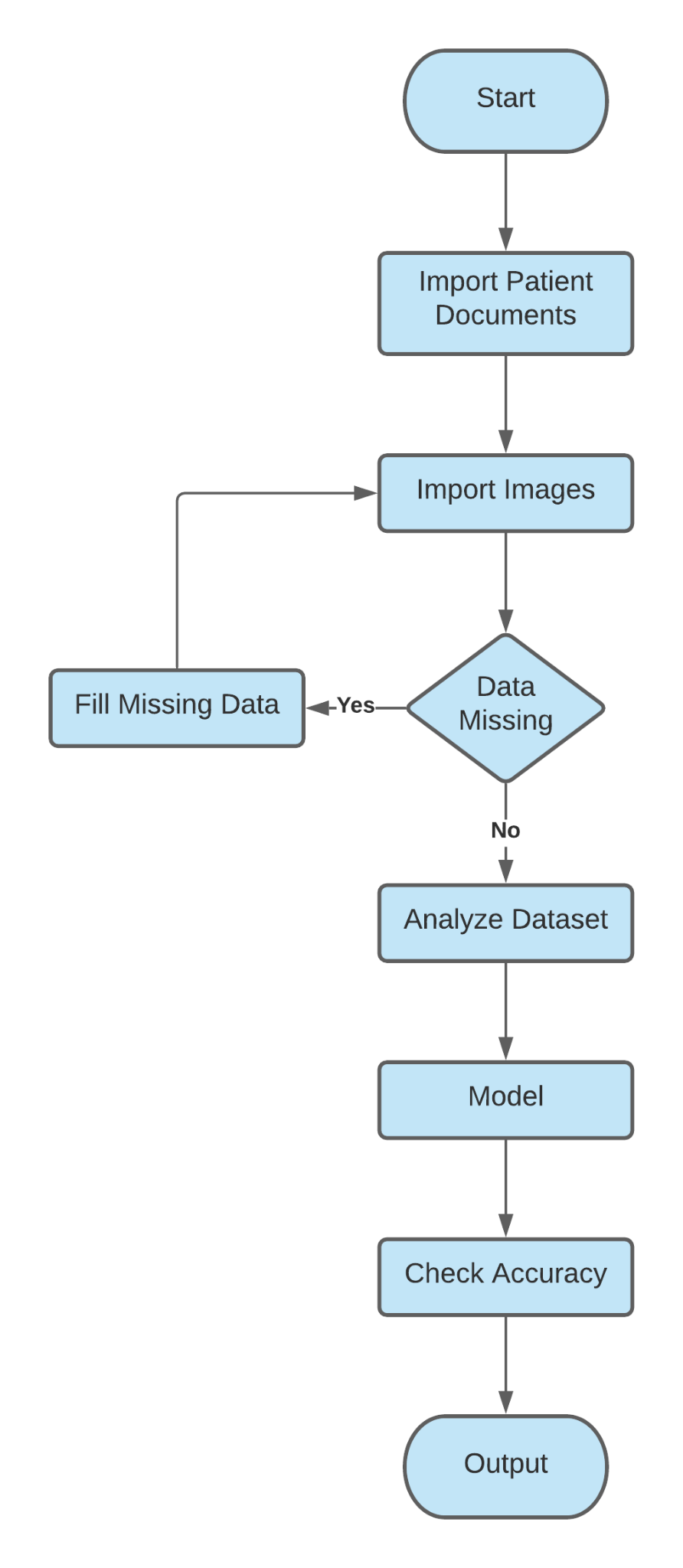
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Figure: System Flowchart

**Dataset**

We obtained a public dataset from the ISIC website for skin cancer classification. We used the ISIC Archive Downloader to download the images. We will use 70% images for training and 30% images for validation of size 224\*224 pixels.

Link: <https://www.isic-archive.com/>

**Review of existing similar systems**

There has been a lot of work published in skin cancer classification using deep learning and computer vision techniques. These works use many different approaches, including type only, segmentation and detection, image processing using other filters, etc.

|  |  |  |  |
| --- | --- | --- | --- |
| **YEAR** | **AUTHOR** | **PURPOSE** | **ACCURACY** |
| **2016**  **[12]** | 1. V. Pomponiu | Deep neural networks for skin mole lesion classification. | **93.64** |
| **2017**  **[13]** | 1. N. C. Codella | Deep learning ensembles for melanoma recognition in dermoscopy images | **93.1** |
| **2018**  **[14]** | 1. H. A. Haenssle | diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. | **--------** |
| **2017**  **[10]** | 1. L. Bi | Automatic skin lesion analysis using large-scale dermoscopy images and deep residual networks | **-------** |
| **2018**  **[11]** | 1. S. S. Han | Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm | **-------** |
| **2016**  **[9]** | 1. J. Kawahara and G. Hamarneh | Multi-resolution-tract cnn with hybrid pretrained and skin-lesion trained layers. | **79.5** |
| **2017**  **[8]** | 1. A. R. Lopez | Skin lesion classification from dermoscopic images using deep learning techniques | **81.33** |
| **2016**  **[15]** | 1. E. Nasr-Esfahani | 1. Melanoma detection by analysis of clinical images using convolutional neural networks | **81** |

**(Esteva et al., 2017)** separately used AdaBoost to classify skin lesions.

**(Xu et al., 2014)** used different sets of features, including the type of lesion, texture, color, etc., and neural networks to make a robust diagnosis system. The examples only showed algorithms using traditional machine learning techniques, but lately, deep learning has proved to be more accurate.

**Skin Cancer Classification**

Several factors can make skin cancer recognition a challenging task. Some of these factors include flaws in image quality like uneven brightness, obstruction, and the fact that many images have a similar shape, color, and texture.

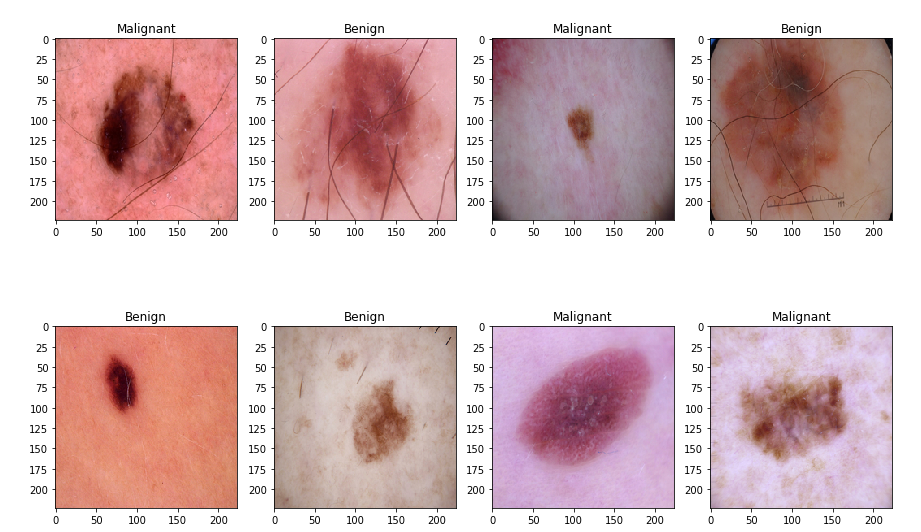


Figure: Dataset Images[19]

**Process Flowchart**

We will follow the following steps to train & test our model.

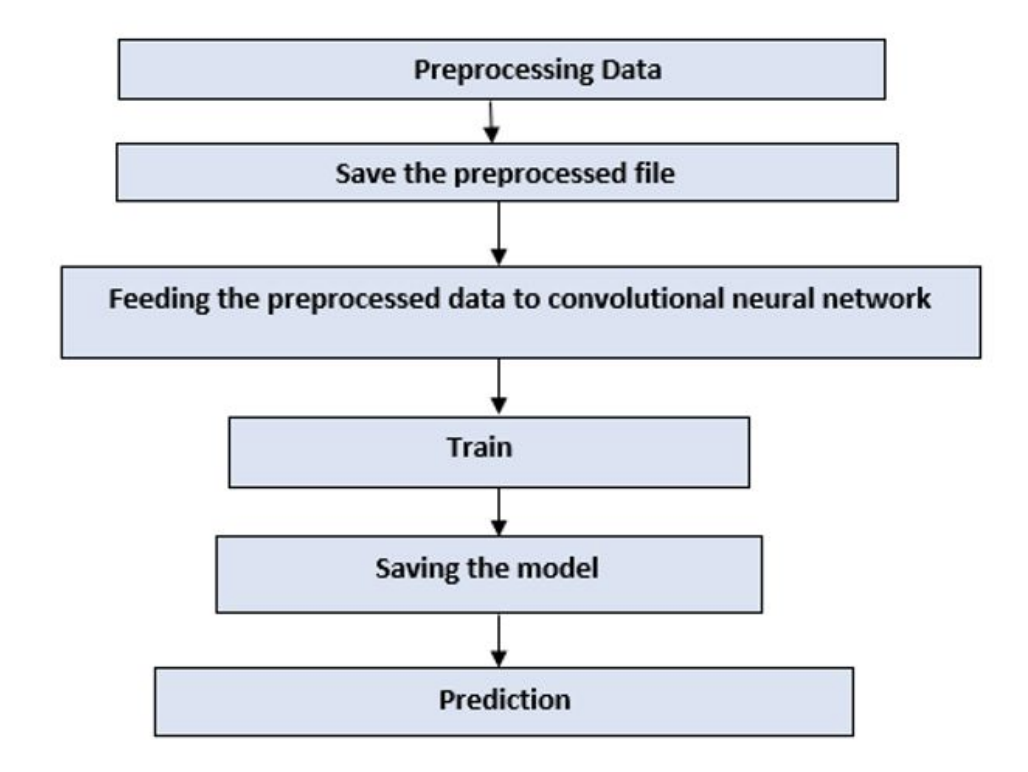
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Figure: Process Flowchart

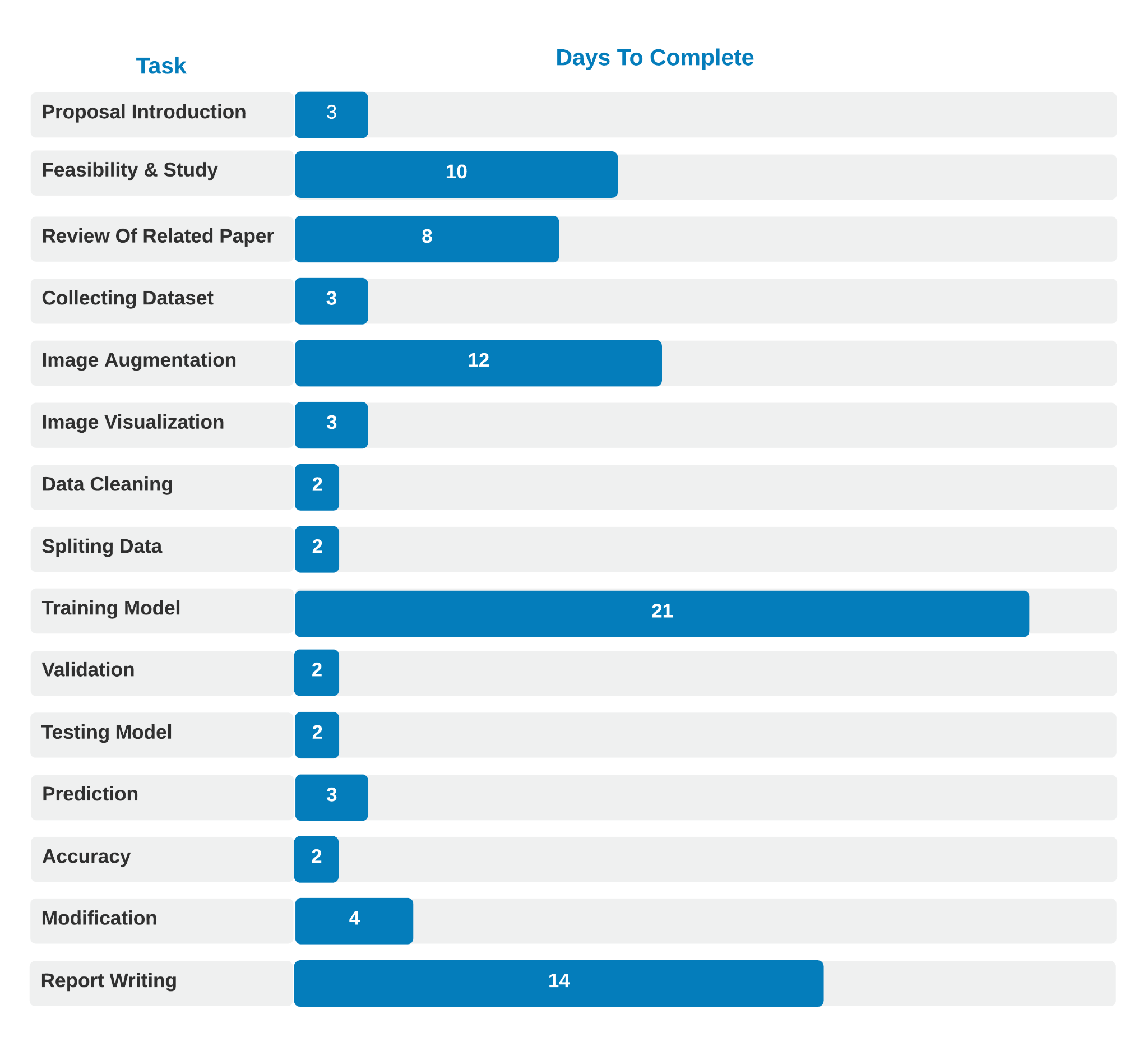
**Required software tools**

1. Jupyter Notebook
2. Numpy
3. Pandas
4. Scikit-image
5. Matplotlib
6. Scikit-learn
7. Keras

**Approximate Costing**

As the software & tools we are going to need in this project are available on the website. Moreover the dataset for this project is also available on the web. Hence, we don’t need any financial support to complete this research based project. But, in future when we will build & launch our software then we may need financial support.

**Project Timeline**

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**Future Work**

Our future plan will be to build a software based on this deep learning model. The software will help the people to detect skin cancer in their preliminary stage.

**Conclusion**

Melanoma cancer is cancer that is difficult to detect in an

ordinary way. Besides being a person with melanoma cancer

does not feel pain, the form of melanoma cancer is also

similar to ordinary moles. In the case of melanoma cancer,

the damage to DNA is caused by overexposure to ultraviolet

rays (UV), and the affected cells are the melanocytes that

produce melanin (pigmentation of the skin).[7]

In conclusion, this study will investigate the ability of deep convolutional neural networks in the classification of benign vs malignant skin cancer.We Will try to show that with use of very deep convolutional neural

networks using transfer learning and fine-tuning them on dermoscopy images, better diagnostic accuracy can be achieved compared to expert physicians and clinicians.[1]

**Bibliography**

1. [**https://www.sciencedirect.com/science/article/pii/S2352914819302047**](https://www.sciencedirect.com/science/article/pii/S2352914819302047)
2. [**https://www.skincancer.org**](https://www.skincancer.org/skin-cancer-information/melanoma/)
3. [**https://en.wikipedia.org/wiki/Machine\_learning**](https://en.wikipedia.org/wiki/Machine_learning)
4. [**https://en.wikipedia.org/wiki/Deep\_learning**](https://en.wikipedia.org/wiki/Deep_learning)
5. [**https://www.simplilearn.com/tutorials/deep-learning-tutorial/what-is-deep-learning**](https://www.simplilearn.com/tutorials/deep-learning-tutorial/what-is-deep-learning)
6. [**https://www.quora.com/What-is-a-convolutional-neural-network**](https://www.quora.com/What-is-a-convolutional-neural-network)
7. [**https://sci-hub.se/https://ieeexplore.ieee.org/abstract/document/9034624**](https://sci-hub.se/https://ieeexplore.ieee.org/abstract/document/9034624)
8. **A. R. Lopez, X. Giro-i Nieto, J. Burdick, and O. Marques. Skin lesion classification from dermoscopic images using deep learning techniques. In 2017 13th IASTED international conference on biomedical engineering (BioMed), pages 49–54. IEEE, 2017.**
9. **J. Kawahara and G. Hamarneh. Multi-resolution-tract cnn with hybrid pretrained and skin-lesion trained layers. International workshop on machine learning in medical imaging, pages 164–171.Springer, 2016.**
10. **L. Bi, J. Kim, E. Ahn, and D. Feng. Automatic skin lesion analysis using large-scale dermoscopy images and deep residual networks. arXiv preprint arXiv:1703.04197, 2017.**
11. **S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang. Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. Journal of Investigative Dermatology, 138(7):1529–1538, 2018.**
12. **V. Pomponiu, H. Nejati, and N.-M. Cheung. Deepmole: Deep neural networks for skin mole lesion classification. In 2016 IEEE International Conference on Image Processing (ICIP), pages 2623–2627. IEEE, 2016.**
13. **N. C. Codella, Q.-B. Nguyen, S. Pankanti, D. A. Gutman, B. Helba, A. C. Halpern, and J. R. Smith. Deep learning ensembles for melanoma recognition in dermoscopy images. IBM Journal of Research and Development, 61(4/5):5–1, 2017.**
14. **H. A. Haenssle, C. Fink, R. Schneiderbauer, F. Toberer, T. Buhl, A. Blum, A. Kalloo, A. B. H.Hassen, L. Thomas, A. Enk, et al. Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists. Annals of Oncology, 29(8):1836–1842, 2018.**
15. **E. Nasr-Esfahani, S. Samavi, N. Karimi, S. M. R. Soroushmehr, M. H. Jafari, K. Ward, and K. Najarian. Melanoma detection by analysis of clinical images using convolutional neural networks. In 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 1373–1376. IEEE, 2016.**
16. [**https://en.wikipedia.org/wiki/Melanoma**](https://en.wikipedia.org/wiki/Melanoma)
17. [**https://www.sciencephoto.com/media/904350/view/malignant-melanoma\**](https://www.sciencephoto.com/media/904350/view/malignant-melanoma%5C)
18. [**https://www.researchgate.net/publication/340880583\_Analyzing\_Lung\_Disease\_Using\_Highly\_Effective\_Deep\_Learning\_Techniques**](https://www.researchgate.net/publication/340880583_Analyzing_Lung_Disease_Using_Highly_Effective_Deep_Learning_Techniques)
19. [**https://www.isic-archive.com/**](https://www.isic-archive.com/)
20. [**https://www.researchgate.net/publication/285688871\_Diagnosis\_of\_skin\_cancer\_using\_image\_processing**](https://www.researchgate.net/publication/285688871_Diagnosis_of_skin_cancer_using_image_processing)
21. **S. Ogden and N. R. Telfer, “Skin cancer,” Medicine (Baltimore) 37(6), 305–308 (2009).**
22. **A. O. Berg, D. Best; US Preventive Services Task Force, “Screening for Skin Cancer: recommendations and rationale,” Am. J. Prev. Med. 20(3 Suppl), 44–46 (2001).**