

GPU based Instantaneous Melanoma Detection and its Comparison with CPU based Approach

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Abstract— Melanoma is recognized as one of the most dangerous type of skin cancer. A novel method to detect melanoma in real time with the help of Graphical Processing Unit (GPU) is proposed in this work. Existing systems can process medical images and perform a diagnosis based on Image Processing technique and Artificial Intelligence. They are also able to perform video processing with the help of large hardware resources at the backend. This incurs significantly higher costs and space and are complex by both software and hardware. For the proposed work, the difference with existing system is that, it can work on a Graphical Processing Unit (GPU) of a simple desktop system. Graphical Processing Units have high processing capabilities compared to a Central Processing Unit of a system. A GPU is composed of hundreds of cores that can handle thousands of threads simultaneously whereas a CPU can only handle a few of them at a time. Various approaches were used for implementing real time detection of Melanoma. The results and analysis based on various approaches and the best approach based on our study is discussed in this work. A performance analysis for the approaches on the basis of CPU and GPU environment is also discussed. All the proposed methods are Deep Learning based methods. The proposed system will perform real-time analysis of live medical video data and performs diagnosis. The system when implemented yielded an accuracy of 90.133% which is comparable to existing systems.

Index Terms— Biomedical, Cancer Detection, CNN, Disease Detection, Deep Learning, GPU, Melanoma, Realtime Detection, Skin Cancer

1 INTRODUCTION

THE early diagnosis and detection of diseases with the help of computer aided systems is getting more prominence every day. It is like at someday in future, computer systems may take over this area reducing the workload of a doctor. Existing systems can process medical images and perform a diagnosis based on Image Processing technique and Artificial Intelligence. Such systems perform processing with the help of large complex systems at the backend. This results in a higher cost for data processing. Graphics Processing Unit (GPU) is a new technology capable for finding out solutions to the computational problems in all the engineering and medical fields. In the medical industry, It supports the processing of higher dimensional data. GPU computation has provided a huge edge over the central processing units (CPU) with respect to computation speed. It is highly parallel, multithreaded, consists of multiple core processors and has high memory bandwidth to give the solution to the computational problems. A reason for the evolution of powerful GPUs are the constant demand for greater realism in computer applications. During the past few decades, the computational performance of GPUs has increased much more quickly than that of conventional CPUs. Hence it plays a major role in the field of modern industrial research and development. GPU has already achieved a significant speed (2x-1000x) than CPU implementation on various fields.

Cancer in its different varieties is becoming one of the most popular diseases across the world. Early detection and diagnosis is crucial in case of survival for this type of diseases. A variety of machine learning tools including Artificial Neural Networks (ANNs), Bayesian Networks (BNs), Support Vector Machines (SVMs) and Decision Trees (DTs) have been widely applied in cancer research for the development of predictive models, resulting in effective and accurate decision making.

Human malignant melanoma is a highly metastatic cancer type that is substantially resistant to standard therapeutic modalities. Although the survival rate of melanoma patients has been improved over the past decades melanoma risk and overall mortality escalate yearly. As per a survey conducted by World Health Organization (WHO) [1], It is estimated that between 2 and 3 million non-melanoma skin cancers and 132,000 melanoma skin cancers occur globally each year. The studies done by American Cancer Society (ACS) [2] predicts that about 91,270 new melanomas will be diagnosed in 2018 at USA (about 55,150 in men and 36,120 in women). It also states that about 9,320 people of these are expected to die of melanoma (about 5,990 men and 3,330 women). These rates have been rising for the last 30 years and this shows the importance of addressing this issue. Diagnosing melanoma can be a complex task. An article in the Journal of Investigative Dermatology [3], explains the complexity of the clinical process of diagnosing melanoma, it involves several skin examination components such as anamnestic data (medical history), comparative and differential recognition as well as pattern analysis. The manual detection can be a lengthy process and it requires highly trained dermatologists. The accuracy of dermatologists is estimated to be about 75 to 85% Most of these deaths due to melanoma are occurring because of the failure to detect it on the right time. If melanoma is recognized and treated early, it is almost always curable, but if it is not, the cancer can advance and spread to other parts of the body, where it becomes hard to treat and can be fatal.

GPUs together with deep learning approaches can be of great help in developing a real time detection system for these kind of diseases. The detection of these diseases, as said earlier, is done by a system with the help of machine learning tools. A GPUs contribution comes here as it saves on the training time

of these machine learning tools by significant margin as compared to normal systems running on CPUs. Deep Learning plays a vital role in the early detection of cancer. This type of diseases requires detection and treatment at right time. It is also very difficult to detect cancerous growths at their earlier stages by human observation. As per the studies conducted by NVIDIA [4] deep learning helped to reduce the error rate on breast cancer detection by 85%. Fortunately, deep learning has shown capabilities in achieving higher diagnostic accuracy results in comparison to many domain experts. While this may be an issue of contention with physicians, for many would-be victims the technology cannot come soon enough. Hierarchical or structured deep learning is a modern branch of machine learning that was inspired by the human brain. This technique has been developed based on complicated algorithms that model high-level features and extract those abstractions from data by using neural network architecture that is similar but much more complicated.

The existing systems [5-9] identifies identify diseases from images. The proposed work aims at identifying diseases from live footages. The use of GPU accelerated computing techniques based on Compute Unified Device Architecture (CUDA) and TensorFlow to speed up the processing is proposed. A machine learning framework, which will be fine tuned to analyze the frames of video, based on Convolutional Neural Network (CNN) is also proposed in this work. The objective of the proposed work is to develop a real time system that takes live footage as input, then analyze this footage to detect any malicious tumorous or cancerous growths, then identify and indicate the affected path, then finally identify and provide the type and severity of disease.

2 AREA OF RESEARCH

Deep Learning plays a vital role in the early detection of cancer. This type of diseases requires detection and treatment at right time. It is also very difficult to detect cancerous growths at their earlier stages by human observation. As per the studies conducted by NVIDIA [3] deep learning helped to reduce the error rate on breast cancer detection by 85%. In addition to being the second leading cause of death (responsible for 8.8 million deaths worldwide in 2015), cancer also has significant and increasing impacts on economy. In 2010, the total annual cost of cancer was estimated at around \$1.6 trillion. But the good news is that early detection can save not only billions of dollars but countless lives. Fortunately, deep learning has shown capabilities in achieving higher diagnostic accuracy results in comparison to many domain experts. While this may be an issue of contention with physicians, for many would-be victims the technology can't come soon enough.

Medical images such as MRIs, CT scans, and X-rays are among the most important tools doctors use in diagnosing conditions ranging from spine injuries to heart disease to cancer. However, analyzing medical images can often be a diffi-

cult and time-consuming process. This time can be reduced by proper utilization of GPU computational power. This work aims at using GPU-accelerated deep learning to automate analysis and thereby increase the accuracy of diagnosticians. GPU-accelerated computing is the use of a graphics processing unit (GPU) together with a CPU to accelerate deep learning, analytics, and engineering applications. GPU-accelerated computing offloads compute-intensive portions of the application to the GPU, while the remainder of the code still runs on the CPU. From a user's perspective, applications simply run much faster. A simple way to understand the difference between a GPU and a CPU is to compare how they process tasks. A CPU consists of a few cores optimized for sequential serial processing while a GPU has a massively parallel architecture consisting of thousands of smaller, more efficient cores designed for handling multiple tasks simultaneously.

3 MATERIALS AND METHODS

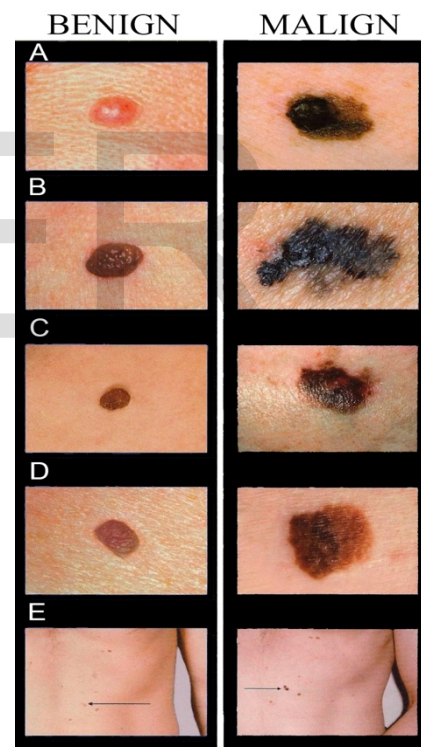


Figure 1. Benign v/s Malign Pigmentations based on ABCDE Method

Most of the melanomas on first look resembles very close to that of normal skin pigmentations or pimples. This makes it really confusing and hence sometimes it is very difficult to identify the skin pigmentation in our body as malign or benign. Using an automated system that will closely observe different cases and learn from them will help for early diagnosis and accurate detection of melanoma.

A most commonly used clinical method for distinguishing melanoma is the 'ABCDE' method [10] shown in Figure 1. The ABCDE criteria were intended as a simple tool that could be

implemented in daily life, a mnemonic “ as easy as ABC ” to alert both the layperson and primary care physician to the clinical features of melanoma. It was introduced in 1985 as a method for diagnosing melanoma. ABCDE acronym stands for Asymmetry, Border Irregularity, Color, Diameter and Evolving. When it was initially introduced, it was only ABCD. Later ‘E’ was added into the acronym in 2004. These parameters have been widely used by Dermatologists to diagnose melanoma. Each criteria has certain features that are recognized to classify melanoma into benign and malignant.

This method is a generally applicable and precise method. But there are some special cases where this method also fails. Such as, If the melanoma is having a very small diameter then it violates the conditions about melanoma stated as per this method. Also there are cases where birth marks are misidentified as melanoma as per the guidelines of this method. So this means although these kind of methods have improved easiness in differentiating malign and benign moles. But there are still chances for wrong diagnosis of moles.

4 PROPOSED SYSTEM ARCHITECTURE

The architecture of the proposed system is shown Figure 2. The system takes live video footages or real time video captured by a camera device as input. This live footages is analyzed for the detection of melanoma using deep learning framework based on CNN. It does this through a combination of filters using machine learning, image recognition and extraction of global and local features.

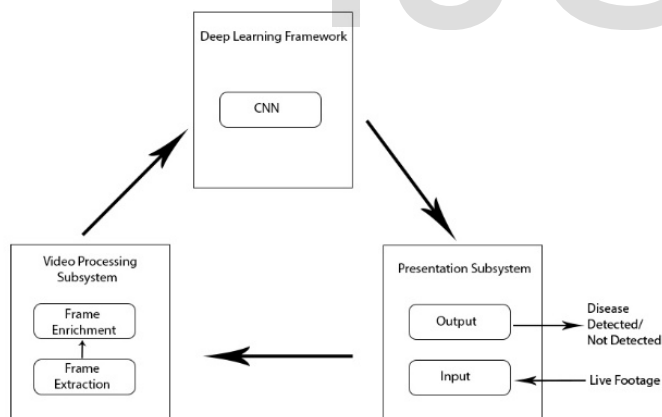


Figure 2. Proposed System Architecture

The proposed system is divided mainly into three subsystems,

Presentation Subsystem: This subsystem captures the real-time frames and passes it to other subsystems for processing. It also presents the output of the real-time analysis to the medical examiner. The most challenging aspect here is that the presentation should not introduce any delays, which would make the system unsuitable for live examinations.

Video Processing Subsystem: Video processing subsystem is responsible for performing the frame extraction from the input footage. It is responsible for handling for enhancing and processing it. This step includes enrichment of the frame by removing noises, improving the contrast etc. and thus improving the overall quality. This subsystem makes use of OpenCV 3.0 and FFMPEG 3.4.2 libraries for implementing frame extraction and enrichment process.

Deep Learning Framework: The deep learning framework consists of convolutional neural network. Regular neural networks do not scale well into images. But convolutional neural network architectures make the explicit assumption that the inputs are images, which allows us to encode certain properties into the architecture. The proposed system is implemented with 2 different types of convolutional networks and performance is analysed for them.

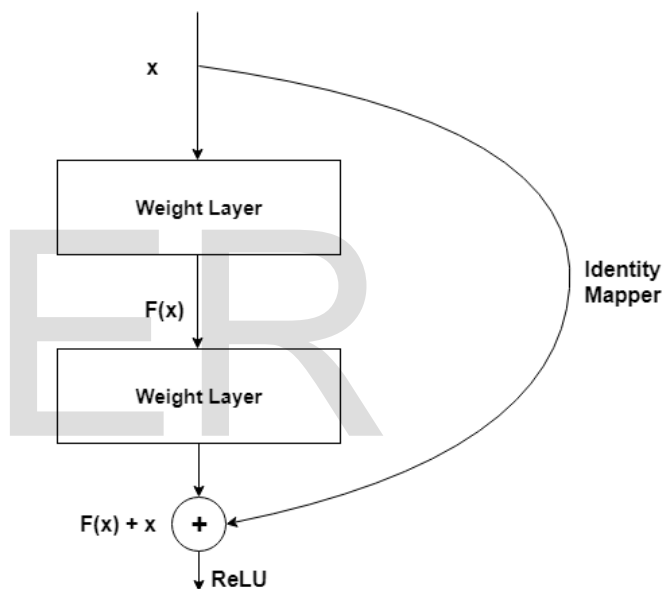
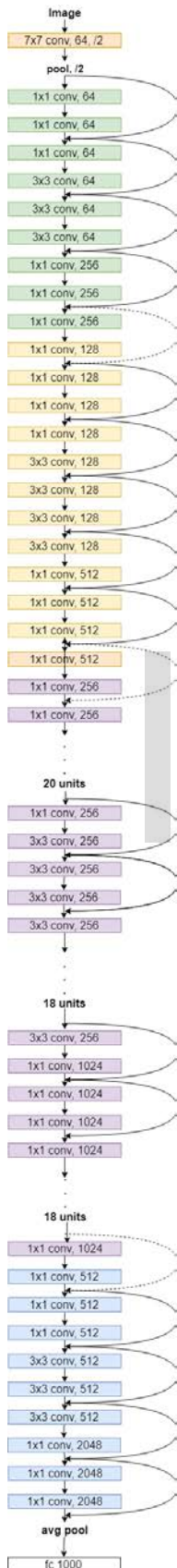


Figure 3. Building Block of a ResNet

ResNet: ResNet is short for Residual Neural Networks which were introduced in late 2015 by Microsoft. It is a type of Convolutional Neural Network used for image recognition. It consists of hundreds of layers. The main disadvantage of deep convolutional neural networks such as U-net is the degradation problem. Degradation problem is caused due to the increase in the depth of network, as a result the accuracy gets saturated and then degrades rapidly. This kind of degradation is not caused by overfitting further increase in layers will result in increase in training error. This problem is addressed by ResNets by the introduction of identity shortcut connections or identity mapping as shown in Figure 3. Normal CNNs will be having direct mapping, where the output of a layer is $F(x)$, instead of using identity mapping, where the output of a layer is given as $F(x) + x$. Here x denotes the identity mapper value.

Figure 4. ResNet 101 Architecture



A trend observed in ResNet as mentioned by He et al.[12] is that as it goes deeper or increasing number of layers is actually reducing the error rate as compared to plain networks where it happens the opposite. So learning is better in RCNN which has more stacked layers as compared to others. Also the performance is better with the use of powerful GPU and more data.

The building block of a ResNet is mathematically represented as,

$$y = F(x, \{W_i\})f(x)$$

where x and y denote the corresponding input and output of the layers. $F(x, \{W_i\})$ denotes the residual mapping. For the example shown in Figure 4. $F = W_2\sigma(W_1x)$ in which σ denotes ReLU.

The proposed ResNet is shown in Figure 4. It consists of 5 set of convolution layers. The detailed specification is as shown in Table 1. The convolutional units in these 5 layers together contribute 101 layers.

Layer Name	Output Size	No. of Units
Convolution Layer 1	112x112	[7x7, stride 2, channel 64] x 1
Convolution Layer 2	56x56	[3x3 max pool, stride 2] x 1 [1x1, channel 64] x 3 [3x3, channel 64] x 3 [1x1, channel 256] x 3
Convolution Layer 3	28x28	[1x1, channel 128] x 4 [3x3, channel 128] x 4 [1x1, channel 512] x 4
Convolution Layer 4	14x14	[1x1, channel 256] x 23 [3x3, channel 256] x 23 [1x1, channel 1024] x 23
Convolution Layer 5	7x7	[1x1, channel 512] x 3 [3x3, channel 512] x 3 [1x1, channel 2048] x 3
Output	1x1	Average pool, 1000d-fc, softmax

Table 1. ResNet 101 Specification

5 RESULTS AND DISCUSSIONS

The dataset used by the system is obtained from the International Skin Image Collaboration (ISIC) archive. 956 images of both benign and malign cases are collected from the archive. These images are used for training the system. Original sizes of images vary from 1022×767 to 4288×2848 pixels. Clinical examination videos related to melanoma are used for testing purposes. The system was tested on 10 persons each with melanoma and without melanoma to ensure the realtime detection capability of the system. For other evaluation purposes such as comparison U-net an ResNet model 20 videos were used for testing with each of one having 16 to 30 instances of melanoma in each of them. Tests were conducted on systems with U-net as well as ResNet and also in a Non-GPU and GPU accelerated environment. The GPU Accelerated environment included TensorFlow for GPU, OpenCV 3.0, Python 3.6 and NVIDIA CUDA Toolkit 9.0 along with an NVIDIA GeForce GTX 1080 Titan Series 4GB DDR5 GPU and Intel Core i7 7th Generation CPU on an ASUS ROG Strix Laptop with 8GB RAM. The Non-GPU environment was setup on TensorFlow, OpenCV 3.0 and Python 3.6 running on an Apple Macbook with 8GB RAM and an onboard Intel HD Graphics 6000 chip-set.

Figure 5 denotes the graph showing number of step per second in a GPU accelerated environment. It is evident from the graph that each step takes less than 0.8 seconds in a GPU accelerated environment whereas compared to a CPU environment as shown in Figure 6, each step is taking around 42 seconds to complete.

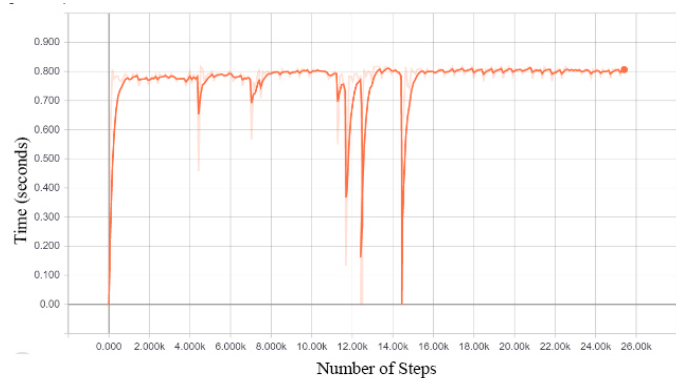


Figure 5. This figure shows the graph which denotes the time taken for each step of the training to complete in a GPU Accelerated environment. The x-axis denotes the number of steps and the y-axis denotes the time taken for each step to complete.

In GPU accelerated system. In every minute, approximately ≥ 75 steps are completed whereas in CPU environment, it is only 2.333 steps per minute. So the GPU Accelerated system is about 32.147 times faster than the system in CPU environment.

Video Sample	No. of. Malign Instances	No. of. Benign Instances
Sample 1	26	4
Sample 2	22	6
Sample 3	22	2
Sample 4	11	7
Sample 5	18	12
Sample 6	13	8
Sample 7	15	8
Sample 8	17	11
Sample 9	9	9
Sample 10	11	11
Sample 11	14	7
Sample 12	20	0
Sample 13	21	5
Sample 14	19	6
Sample 15	0	16

Table 2: No of Malign and Benign instances in each test input videos

For the real-time testing, 20 specimens were used in which 10 were malign and 10 were benign. For the benign samples, one of them was misclassified and rest of 9 were correctly classified. For the malign samples, only one of them was misclassified and rest of 9 were correctly classified. The sensitivity and specificity of the system were calculated as 0.9. The system is giving an accuracy of 90% which is a similar accuracy to that of existing methods. But the system is expected to give a better accuracy when trained with a larger dataset and tested with better test samples. The quality of the test samples were not the best and was only satisfactory. However, the proposed system is about 32 times faster than existing methods.

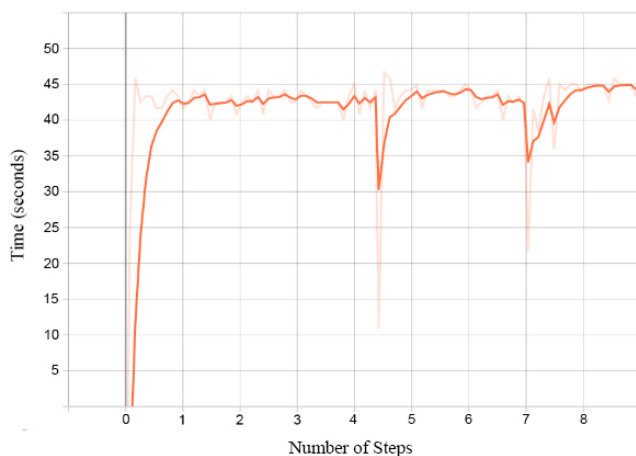


Figure 6: This figure shows the graph which denotes the time taken for each step of the training to complete in a CPU only environment. The x-axis denotes the number of steps and the y-axis denotes the time taken for each step to complete

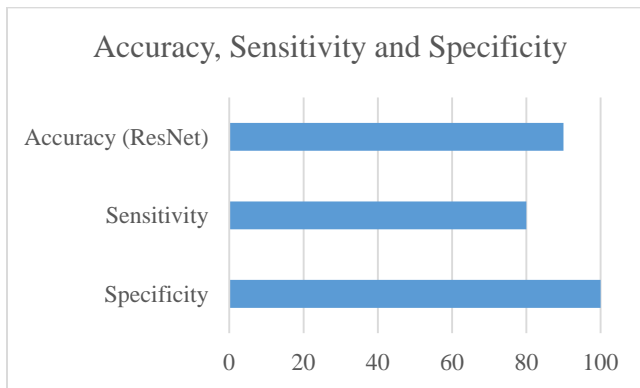


Figure 7: Figure shows the accuracy, sensitivity and specificity parameters for the convolutional neural network ResNet which was the one that shown better performance on the comparisons performed.

5 CONCLUSION

The proposed work is a GPU accelerated system for the fast, accurate and real-time detection of melanoma using deep learning framework is proposed. Two variants of deep convolution networks were used in implementation of the system. Experimental results indicate that among two systems implemented, the one with Residual Neural Networks are having better accuracy of 90.133% compared to that of system implemented with U-net which is having an accuracy of 89.066%. Training phase of these system used images from International Skin Image Collaboration archives and testing were performed on human specimens. Detection of melanoma was performed by the system without any lesion segmentation or image pre-processing techniques. The system performed classification by processing frames which were extracted from the real-time input feed obtained by the system from the live camera. The system implemented performs real time detection from live input video feeds and is much better as compared to existing systems which uses image processing techniques to pre-process which takes melanoma images as input. So the proposed system performs video processing as compared to existing system which performs image processing. The GPU acceleration performed on the system increases the speed of computation and thus improves the ease of use, speed and provides the capability of fast detection for the system. The results obtained from the system are comparable to the state-of-the-art systems with the proposed system giving an accuracy of 90.133%.

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