Convolutional Neural Network-based medical checkup system for Pigmented Skin Lesions Classification.

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Statement of originality

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Abstract

The objective of the research is to develop an artificial intelligence-based automated system for detection of pigmented skin lesions for people with less mobility. The study involves experiments with different architectures of convolutional neural networks and understanding the effects of hyper-parameters on developing deep learning model. The results obtained from tests performed during the development of intelligent models were compared with predicted resulted in lesions by medical professionals.

Contents

Acknowledgements

I want to express my gratitude to my supervisor Dr David Croft for guiding me thought the investigations. The support of all medical professionals who contribute by providing data to the research is sincerely acknowledged. At last, I would thank my parents, who supported me finically and psychologically throught this journey of computer science.

Chapter 1

Introduction

1.1 Introduction to Problem

Skin cancer is categorized into two types: melanoma and non-melanoma skin cancer. Melanoma, is the most dangerous kind of skin cancer accounted for an estimated 16,000 deaths each year from 2014 to 2016 in the United Kingdom (Cancer Research UK, 2020). The melanoma tumor caused by melanocytes can result in uncontrolled and abnormal growth which can spread in the human body (Korotkov and Garcia, 2012). Detection and classification of unknown pigmented skin lesions can result in early diagnosis of the medical problem. The research data provided by a cancer research organisation in 2017 has shown that melanoma was the 20th most common disorder with new incidents of 81,00 and 83,00 in males and females respectively in the United Kingdom (Korotkov and Garcia, 2012). Dermoscopy is a non-invasive method of examining the pigmented skin, which includes microscopic imaging of the surface structure of pigmented skin lesions (Korotkov and Garcia, 2012). Early diagnosis of pigmented skin lesions is crucial to classify skin disorders to decrease mortality concerning particular skin disorders. Dermoscopy improves the detection of melanoma compared to the detection of disease with naked eyes by analysing the pigmented skin lesion. Previous studies have shown that such tumours can result in higher chances of better treatment and cure of disease by removing the tumour (Celebi et al., 2007). The current diagnosis method of detection involves using ABCD rule which considers the Asymmetry, Border irregularity, Colour irregularities, Darmascopic structures respectively of common pigmented skin lesions (Loescher et al., 2013). People working in busy work environments or less mobility can be victims of belated and slow diagnosis of such dangerous skin cancers. The automated analysis of pigmented skin lesions using artificial neural networks can be beneficial in the optical analysis of microscopic images of pigmented skin lesions. The primary targeted audience who benefits from the outcome is the people who are working in busy work environments or people with less mobility are best to use cases that can use such an automated

system. Booking a prior appointment with medical professionals based on the urgency of detected medical problems can result in the immediate treatment of patients with more critical conditions. The people with less mobility such as older audiences or people with special needs can detect pigmented skin lesions through online systems in an inconvenient manner. Medical institutions can use such technologies to automate the process of pre-health checkups and overcome the problem of shortage of staff members in case of emergency. Such automated systems can also result in the faster diagnosis of medical problems compared to a manual analysis by a clinician. Furthermore, manufacturing companies that supply the microscopic medical instruments can also use such intelligent models with their products to provide value to customers and medical institutions.

1.2 Objective of Research

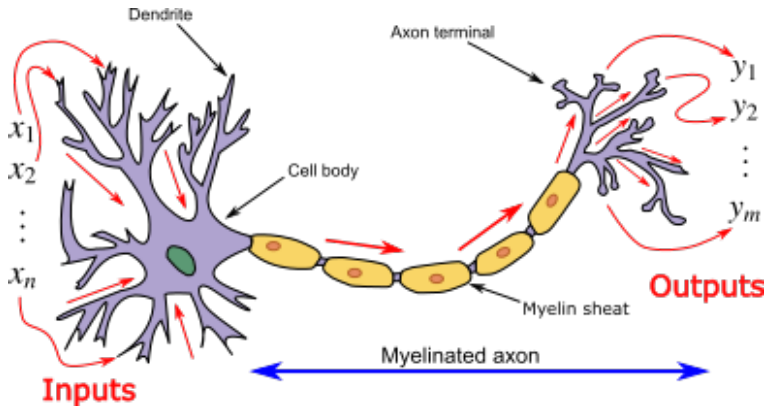
The research concentrates on developing a type of artificial neural network called a convolutional network to perform automated optimal analysis to identify the class of pigmented skin lesions. The research focuses on providing the quantitative analysis on comparing the results predicted by the automated intelligent machine are compared with medical professionals to identify the classes of pigmented skin lesions. The study employs different experiments by applying different model architectures and analysing accurate hyper-parameters for optimal performance. The research concentrate on analyzing limited skin tumors such as melanoma, benign keratosis, melanocytic nevi and basal cell carcinoma. The hypothesis for the research is that the model will perform better than medical professionals in examining the pigmented skin lesions. The investigation employs publicly available HAM10,000 dataset (Tschandl, 2018). The HAM10,000 dataset contains an extensive collection of 10,000 images of labelled data units that were collected from a diverse population of subjects over twenty years. The outcome of the research project will analyse the effectiveness of the automated pigmented lesion system. Furthermore, the intelligent model will be deployed on a web-based system to provide an interface to use the system to analyse by the general audience.

1.3 Perceptron Model

1.3.1 Inspiration from biological Structure of Neurons

The human brain is composed of millions of specialised cell "neurons" which are interconnected to each other which carry electrical and chemical signals from neuron to another to function There are an estimated 500 trillion connections between neurons in the human nervous system which helps communicate signals (Patterson and Gibson, 2017). The inspiration of artifical neural networks are taken from functioning of human brain and learn to recoganise patterns and relationship in the data (Agatonovic-Kustrin and Beresford, 2000).

1.3.2 Neural Structure



The figure above represents the biological structure of neurons that helps in the communication of electric signals in the nervous system to learn and process information. The biological structure of neurons includes three major parts dendrites which are responsible for accepting the electrical and chemical signals to the neuron. Furthermore, the neuron contains the nucleus which is accountable for the processing input information with the neurons. At last, the processed information is passed to another neuron which is interconnected to neurons in the human nervous system through axon terminals (Agatonovic-Kustrin and Beresford, 2000).

1.3.3 Perceptron Model

Perceptron model was proposed by Frank Rosenblatt in 1943 to design the model to mimic the human brain (Kussul et al., 2001). Perceptron model or the single-layered feed forwards network networks take the vectors of inputs and multiply with a randomly initialized weights and add random bias to network and process the information by providing data to the activation function to process the information (Agatonovic-Kustrin and Beresford, 2000).

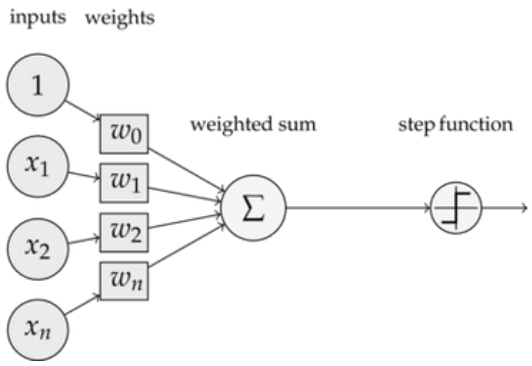


Figure 1.1: Perceptron Model

The figure 1.1 represents the simple perceptron model which consists of inputs x and weights w for which the weighted sum of multiplication result of inputs and weights will be passed to the step activation function.

1.3.4 Mathematical Representation

The equation below represents the preceptron model mentioned above in Mathematical notations.

$$y = \Big[\sigma(\sum_{k=0}^{n} x_k.w_k + b_k)\Big] \tag{1.1}$$

In, equation above $\sigma = Activation function$, x and w represents the inputs provided and weights vectors in the network respectively. Furthermore, symbol b represents the bias in the equation, during the optimization of the network weights and bias are adjusted accordingly to improve the predection. There are various activation functions σ such as step function sigmoid, relu, leaky relu and others that can be applied based on the requirements of the model prediction.

1.4 Multi Layered Feed Forward Neural Network

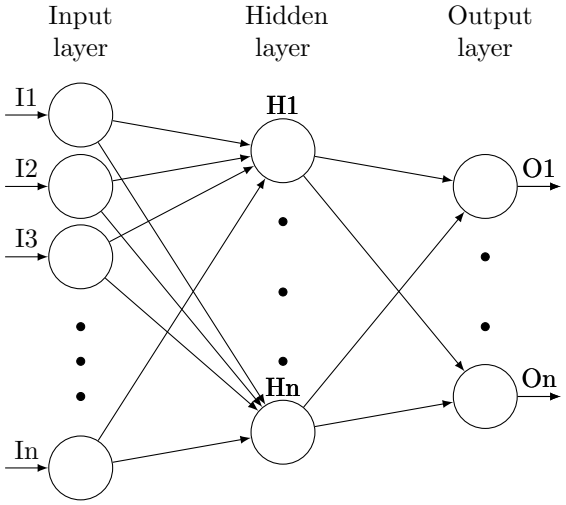


Figure 1.2: Multi Layered Neural Network diagram.

The perceptron model acts as the base for all the functioning of modern multi-layered neural networks. The output of the single neuron described in the above perceptron is taken as the input in the next layer of the network. The above figure(1.1) shows an example of multi-layered neural where the first layer is known as the input layer and intermediate layers are called hidden layers and the last layer is known as the output layer. The single neuron can perform limited computation but the computation power increases with inter-connected neurons in the network (Agatonovic-Kustrin and Beresford, 2000) where at each layer information is processed through the appropriate activation function. Artificial neural networks are designed to learn the patterns and relationships in the data and requires enough amount of data to train and predict accurate outputs (Agatonovic-Kustrin and Beresford, 2000). The training data is passed to the neural network to recognize the patterns in data and each iteration or epoch the model prediction gets improved with the optimisation algorithm which propagates through the network to update the weights and bias to increase the accuracy (Agatonovic-Kustrin and Beresford, 2000). The accuracy of the neural networks are determined through various hyper-parameters such as learning rate, number of hidden layers in the model and number of epochs for which the model is trained. The fundamental rule for learning in artificial model

1.4.1 Cost Function and Backpropagation Algorithm

The objective for training deep learning models is to reduce the error in prediction on each iteration and learn data patterns and relationships by increasing the prediction accuracy. Cost function is an appropriate method to analyse the performance of the neural network as it describes how well, model is predicting the actual results. The equation below describes the cost function equation also known as mean squared error (Lubis et al., 2014).

$$c = \frac{1}{2m} \sum_{i=1}^{m} (h - y)^2 \tag{1.2}$$

In, equation(1.2) h is the predected outcome of the intelligent model and y is the actual value of the input. The equation above is mean square of predected value - actual value. The objective of optimisation algorithms is minimise the equation(1.2) to decrease the value of cost function so, the value is close to zero as much as possible so, that predected and actual value are almost same which means overall model accuracy has improved (Lubis et al., 2014). The algorithm which aims to minimise the cost function is gradient descent. Gradient descent algorithm is a optimisation algorithm which is iterative in nature.

$$\frac{\partial}{\partial w} (\frac{1}{2m} \sum_{i=1}^{m} (h - y)^2) \tag{1.3}$$

$$\frac{\partial}{\partial b} (\frac{1}{2m} \sum_{i=1}^{m} (h - y)^2) \tag{1.4}$$

The algorithm functions by finding the partial deravative of the cost function in respect to weights and bias as shown in the equation above. The objective is to find minima of the cost fuction which improves the accuracy (Lubis et al., 2014). Backpropagation utilises the gradient descent algorithm and propgates after each layer to update the bias and weights in backwards direction to improve accuracy of the model.

Chapter 2

Literature Review

2.0.1 Convential Diagnosis Methods

The most common conventional diagnosis method of detection involves using ABCD rule which considers the Asymmetry, Border irregularity, Colour irregularities and Dermoscopic structures respectively of the common pigmented skin lesions (Loescher et al., 2013). The rule for classification was introduced in 1985 as abcd rule and was amended with abcde in 2004 where 'E' reflects the lesions which are evolving. An alternative method of examination of pigmented skin lesions is ugly duckling signs which was introduced to state the limitation of the ABCD rule (Daniel Jensen and Elewski, 2015). The ugly duckling signs state the spot which is unlike other lesions are great suspects of melanoma (Grob and Bonerandi, 1998). Despite the limitations of above methods, both provide a great framework for clinicians and general audiences to spot melanoma based symptoms (Daniel Jensen and Elewski, 2015). Small malignant melanoma are millimeters in size in initial phases of its growth. The micro-melanoma requires more attention to be detected by physicians and researchers believe that small lesions possess challenges for medical professionals to clearly examine malignant based problems (Bono et al., 2004). Dermatoscopy is non-invasive microscopic imaging of pigmented skin lesions which provides clear imaging to perform proper analysis on pigmented skin lesions (Loescher et al., 2013). The study was conducted in Italy for the period of five years in which ninety four melanoma based lesions. Furthermore, results were treated to examine the clinical and dermoscopic features of cutaneous melanoma lesions with maximum diameter of 3mm. The outcome of the research has shown that only samples of twenty two lesions which accounts for 2.4 percent of overall samples were decided based on the clinical size feature of pigmented skin lesions (Bono et al., 2004). Moreover, the research mentions that dermoscopic results are more accurate to diagnose and has been an aid for early detection of melanoma skin cancer provided the clinicians are aware about disease (Bono et al., 2004). The result of dermatoscopic images is examined by dermatologists to classify the pigmented skin lesion. Dermatologists select different approaches to examine pigmented

skin lesions which might include ABCDE rule or ugly duckling signs, where both the methods complement each other to detect pigmented skin lesions. The research proposed an addition of 'F' to mnemonic which uses both current methods ugly duckling sign and ABCDE rule which also account for funny or unlike lesions to be suspect of melanoma based lesion (Bono et al., 2004).

2.0.2 Support Vector Based Machine

Thompson Felsia and Jeyakumar proposed research in 2017 on support vector machine based classifier to detect multi-lesions skin cancer by analysing pigmented skin lesions with an accuracy of 86.37 percent. The proposed investigation with SVM based classifier has performed image segmentation using SRM (support region merging) algorithm. Furthermore, it employs SURF (speed up robust features) to find the region of interest for feature extraction to get optimal classification performance based on vector-based technique (Thompson and Jeyakumar, 2017). However, the research does not include image augmentation which generalises the predictions accurate to test in real-world environment. The research papers mention that support vector machine for automated classification of pigmented skin lesions is sensitive to the artefacts and can potentially increase the false positives which mean that predicted result for analysis was wrong positive prediction instead of an actual negative result. The investigation will perform image augmentation to generate random samples of images with different rotation angle and flipped images will be used to train and test the model to generalise the overall performance.

2.0.3 Border Detection Based System

Rahil Garnavi and his other co-researchers purposed research based on a state of the art border detection method combined with the colour space analysis and clustering-based histogram hybrid thresholding to classify pigmented skin lesions. The research was primarily focused on the research was to develop the hair removal mechanism to perform colour channels transformation. Furthermore, for all the image channels the noise reduction and clustering-based histogram thresholding were performed for optimal border detection. The predicted outcomes of novel border detection system were compared with the borders detected by the actual dermatologists on a sample of dermoscopic pigmented skin lesions to understand the reliability of the system (Garnavi et al., 2011).However, the system was only tested on a data sample set of 30 dermoscopic images and four sample sets of dermatologist hand-drawn images were used as ground truth to compare the results. The system was tested on overall 85 dermoscopic pigmented skin images with high resolution. Border detection can be used to analyse the pigmented skin lesions but convolutional networks have the potential to find more data patterns in the images to minimise the cost function using the backpropagation algorithm. The current research will employe basic image segmentation based on the binary threshold algorithm as an experiment to help network detecting more accurate borders of pigmented skin lesions.

Deep Feature to classify Pigmented Skin lesions

In 2016, a research paper from Simon Fraser University's computer science and medical image analysis lab had researched using deep residual network architecture with ten labelled classes of pigmented skin lesions. The research was based on very deep convolutional network architecture with the accuracy of 85.8 percent in classifying five distinct classes and 81 percent in classifying 10 classes of pigmented skin lesions (Kawahara et al., 2016). Although the performance of the overall convolutional network was accurate, the training and testing data were limited to 13,00 overall images of 10 distinct classes. However, In the current research project, the classes of labelled images will be five and around 9,000 overall images will be used during the investigation. Estimated 80 percent of data will be consumed for training the model, and the rest of the label images will be used as validation and testing datasets to evaluate the performance of the model. Research is also consuming such artificial neural network-based technologies to various areas of investigations.

Chapter 3

Methodology

3.1 Required Installation and Configuration

The research purposes a solution based on deep convolutional neural networks With various experiments mentioned in further sections. The experiments require specific configuration for cuda libraries to run programs on available GPU(Graphical Processing Unit) for faster processing and further, instructions to setup environment can be found at Tensorflow gpu installation guide [1]. Alternatively, the machine learning models can also run without installing cuda libraries on CPU but the processing will be slow. In addition, the convolutional neural network was implemented using Python3 and Jupyter notebooks were used in these experiments which provides an appropriate interface to experiment and write markdowns. Jupyter notebooks can be installed by installing Anaconda [2]. Furthermore, data science and machine learning libraries are required such as Numpy, Keras, Matplotlib and OpenCV. Numpy library is required for performing mathematical operations on multi-dimensional NumPy arrays. The matplotlib library provides an interface to visualise the output results. The OpenCV library was used for image processing in the process of developing an automated system for classifying pigmented skin lesions. Moreover, keras library was used to develop deep convolutional models. HAM,1000 (Human Against Machine, 1000) dataset was used to develop image classifier (Tschandl, 2018). The dataset primarily contains two folders which includes overall 10,000 dermatoscopic images of pigmented skin lesion. In addition, it also contains a csv file which includes the meta-information regarding pigmented skin lesions. The required files can be downloaded from harvard dataverse webiste [3].

[1] `https://www.tensorflow.org/install/gpu`

[2] https://www.anaconda.com/distribution/

[3] `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T`

3.2 Data Processing and Normalisation

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

Figure 3.1: Pandas Dataframe containing information about pigmented skin lesions

The information was read using pandas into the data frame, which is a data structure that allows storing tabular data from CSV files as shown in figure 3.1 which represents the small section of the whole pandas dataframe. The CSV file contains irrelevant information such as age, sex and localisation of patients in the data frame which was removed by dropping the non essential columns.

	lesion_id	image_id	dx	dx_type
0	HAM_0000118	ISIC_0027419	bkl	histo
1	HAM_0000118	ISIC_0025030	bkl	histo
2	HAM_0002730	ISIC_0026769	bkl	histo
3	HAM_0002730	ISIC_0025661	bkl	histo
4	HAM_0001466	ISIC_0031633	bkl	histo

Figure 3.2: Pandas Dataframe containing essential information

The figure 3.2 represents the pandas essential columns as result of elemination of irrelevant information. In addition, the dataset contains unclear and hairy images of pigmented skin lesions which were manually removed from the dataset

to enhance the quality of available data. Furthermore, the research only focuses on limited categories of pigmented skins which results in dropping data columns for the other categories of data. The information shown in 3.2 dataframe contains a lesionid column which coresponds to image names which were were read into numpy array using pillow library from respective directories. The data for convolutional neural networks needs to divided into training and testing data, the model learnings are peformed with learning the patterns and relationships in the training datasets and evaluation of the model is performed on the testing data which is never feed to the intelligent model which training. The dataset was divided into training and testing sets using `sklearn.model_selection.train_test_split` class in the portion of 80 per cent for the training dataset and 20 per cent of testing datasets. The next step towards to preparing the dataset was reading the images data into NumPy array for both training and testing datasets and converting the image names from pandas series to NumPy array corresponding to each image and assign class number based on category of pigmented skin lesion in the dataset. Furthermore, the training and testing datasets were serialised into dictionary in a pickle encoded file. Therefore, the encoded file sizes are compact and are portable in comparison to storing actual image files. [1]

[1] `https://github.coventry.ac.uk/sareenv/Final-Year-Project/blob/master/Research`

3.2.1 Data Normalisation

The images with RGB(Red, Green and Blue) channels information was stored in NumPy multi-dimensional array with numbers ranging from 0 to 255. The NumPy array was converted into the float32 format, and each element of the array was divided by 255 to normalise the data so, that it only ranges between 0 and 1 in float format which will help while training the model. In addition, one hot encoding was performed on class labels of the pigmented lesions. The one-hot encoding is a representation of the categorical variable as binary vector and normalises the categorical labels into a binary vector. One hot encoding was performed to the labels data for each pigmented skin lesions. The data normalisation process will help to train the models as images from training and testing data samples are ranging from 0 to 1 instead of 255 which results in the improved model accuracy.

3.2.2 Image Segmentation

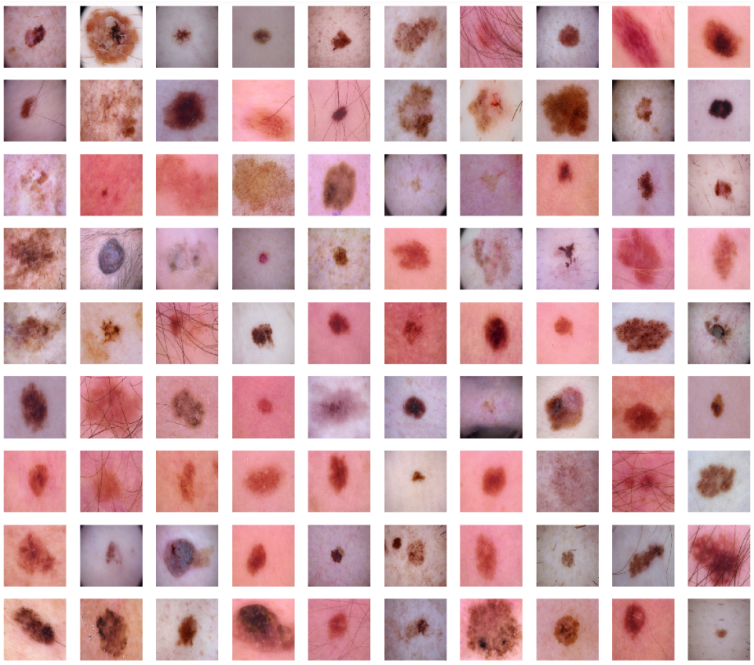


Figure 3.3: Pigmented Skin lesions before Image Segmentation

Figure 3.3 shows the sample from training dataset before performing image segmentation. The figure 3.3 above was plotted using matplotlib library.

3.2.3 Thresholding Segmentation Algorithm

Thresholding is one of the commonly adopted method in image segmentation which helps in descrimination most significant pixels in the images (Al-Amri et al., 2010). The thresold value is selected and the gray scale images are converted into the binary representation of the image and value of image which are greater than the thresold value will be selected with keeping all the attributes of the images such as position and shape (Al-Amri et al., 2010). Thus, reducing the complexity of the image data and making it easier for classification related tasks. Futhermore, the segmented images will be consumed in the model training. The thresholding segmentation was performed using OpenCV library using `cv.threshold(image,0.5,1,cv.THRESH_BINARY)` where threshold value of 0.5 and maximum value of the pixel can be 1 as it was normalised.

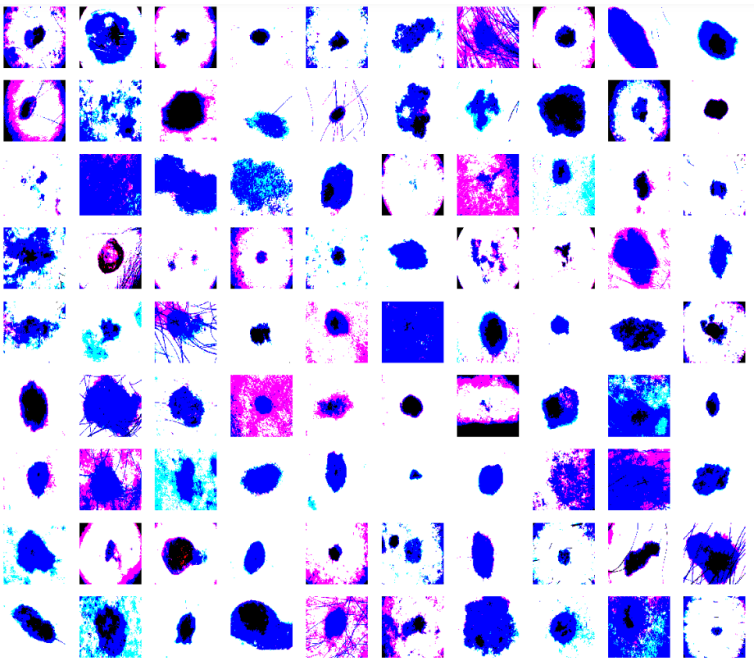


Figure 3.4: Binary Images Segmentated Pigmented Skin lesions

The figure 3.4 shows the result of applying the threshold image segmentation on pigmented skin lesions. The process of image segmentation will simplfy the process of border and edge detection by the convolutional neural network. Figure 3.4 was plotted using matplotlib library.
[2]

[2] `https://github.coventry.ac.uk/sareenv/Final-Year-Project/blob/master/Research`

3.3 Convolutional Model Training

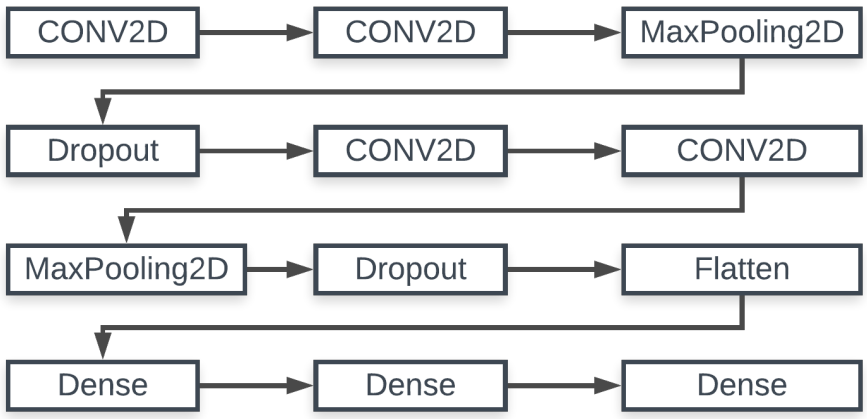


Figure 3.5: Model Architecture 1

The model architecture 3.5 was implemented using the keras Api in which 2 dimensional convolutional layers were added to the sequantial network, where width and height of input image is 224 pixels and the three rgb channels depth are represented by 3. The initial convolutional layers contains 32 input filters with the kernel size of (3, 3) with relu activation function. In the network layers followed by first two convolutional layers are polling layer in the architecture MaxPooling was used to extract maximum of the input features after applying image filter or kernel to the given image of pigmented skin lesions. Furthermore, dropout of 0.4 was used in the network to generialise the overall performance of the network and avoid overfitting of data points. The next two layers in the networks are also another convolutional layers with 64 image filters and similar relu activation function. Similar fashion as aboved was applied to the network with MaxPooling to extract most significant pixels from feature maps followed by the dropout in the network to generialise it. The features extracted by the convolutional layers are flattened into one dimensional array. The flattened array will be passed to the fully connected layers in the neural network to process the information. The model contains three dense hidden layers and one output layer in the neural network. Furthermore, the model architecture was compiled using various hyper-parameters which effects such as learning rate and optimiser for the convolutional model which helps in computing the gradient for the loss function to minimise the error in predecting category of pigmented skin lesion. [3]

[3] `https://github.coventry.ac.uk/sareenv/Final-Year-Project/tree/master/Research`

3.4 Experiments for optimal Model optimiser

The model architecture at initial stage was compiled using different hyper-parameters such as optimal optimiser for the neural network and learning rate. These hyper-parameters can have impact in finding gradient descent of loss function. Keras libraries provides various optimisers such as Adam, SGD and RMSProp Optimiser which aims towards reducing the cost function. The model architecture mentioned above was trained for 30 epochs or iteration to investigate the optimal optimiser for classification of pigmented skin lesions. The model was trained under learning constant rate of 0.001 and loss function of categorical crossentropy because the model has to evaluate the mutiple data classes for pigmented skin lesions.

3.4.1 Adam Optimiser

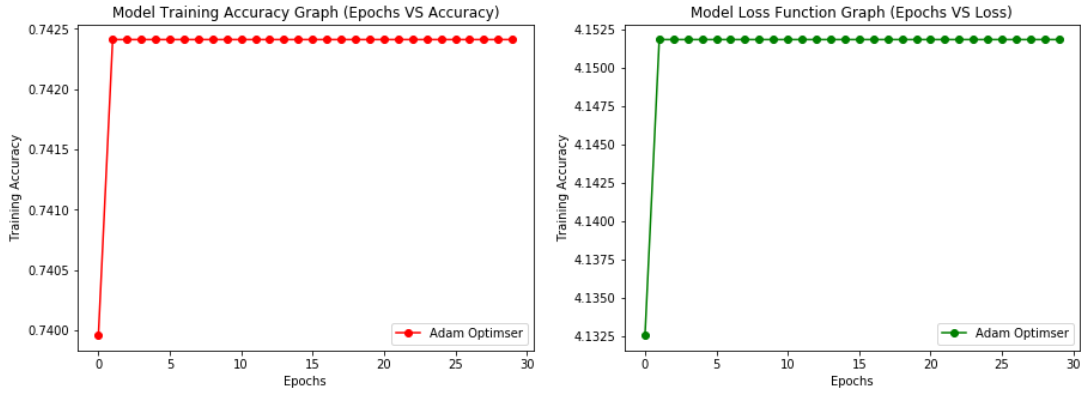


Figure 3.6: Model Results obtained with Adam Optimiser

The figure 3.6 refects the results obtained from training the model using adam optimiser. The figure 3.6 shows that model loss function is not decreasing and after few epochs there was no improvment in model accuracy which means that adam optimiser is sutaible optimiser for model architecture 3.5 presented above.

3.4.2 SGD Optimiser

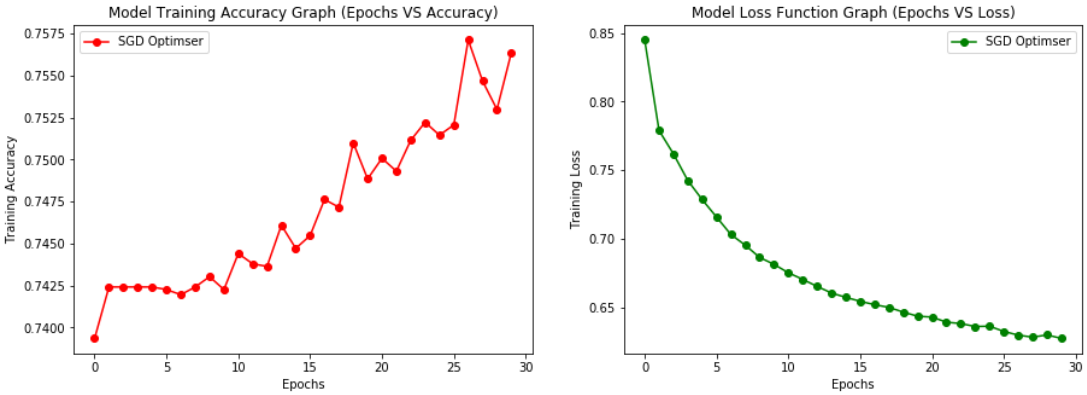


Figure 3.7: Model Results obtained with SGD Optimiser

The figure 3.7 refects the results obtained from training the model using sgd optimiser. The model shows improvment in model performance. The training accuracy of model increased over epochs and loss function was decreasing as anticipated as shown in the figure 3.7 above.

3.4.3 RMSProp Optimiser

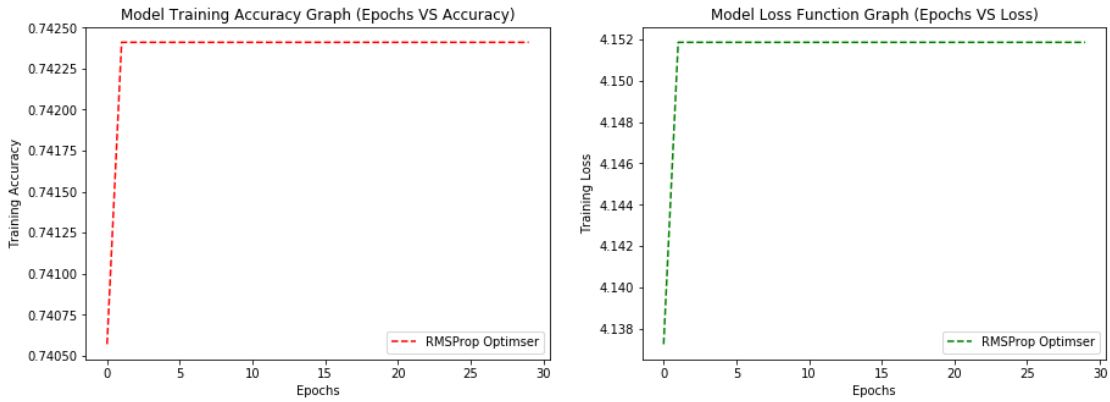


Figure 3.8: Model Results obtained with RMSProp Optimiser

The figure 3.8 refects the results obtained from training the model using 'RMSProp' optimiser. The model performance was similar to the adam optimiser.Therefore, the SGD optimiser was optimial optimiser for classificaiton model under the

constant hyper parameters mentioned above. All further experiments are performed on convolutional neural network are trained on SGD optimiser.

3.4.4 Optimiser Accuracy Results

Optimiser	Learning Rate	Model Accuracy	Epochs
ADAM	0.001	72.79%	30
RMSProp	0.001	72.79%	30
SGD	0.001	75.05%	30

The table above shows the accuracy results obtained from evaluating the trained model on testing data which were trained for 30 epochs or iterations with different optimiser.
[4]

[4] `https://github.coventry.ac.uk/sareenv/Final-Year-Project/tree/master/Research`

3.5 Experiments with Hyperparameters

The experiments were performed on the convolutional model to understand the effects of the hyper-parameters such as learning rate of the network, the number of epochs for which the model for trained and increasing the hidden and convolutional layers. The adjustments to the hyperparameters which were made on the model had an impact on the accuracy of the overall classification of the pigmented skin lesions.

3.5.1 Learning Rate Experiment

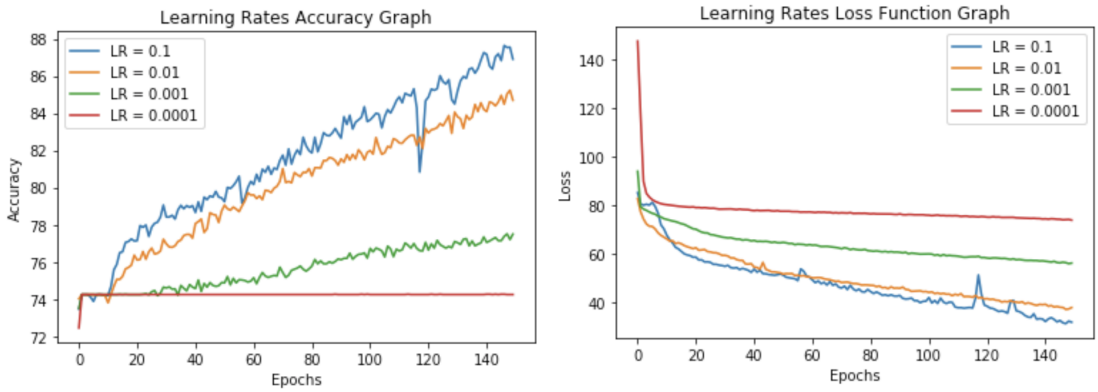


Figure 3.9: Variable Learning Rates

The figure 3.9 above shows that the model was trained for different learning rates as shown in the legend of the figure 3.9 for thirty epochs or iterations. The outcome of the above test was that the model model accuracy of the model were increasing with decrease in the learning rates. The graph obtained shows that the model accuracy was proportional to the learning rate while using SGD optimiser. The figure 3.9 also shows the decline in the loss function for different learning rates in convolutional model trained with SGD optimiser. Therefore, the most optimal learning rate to train the convolutional network neural network was 0.1 and 0.001. During the experiments, it was observed that model with the lower the learning rate consumes more time in the process of training. Further model training experiments are peformed on learning rate of 0.01 to achieve the accuracy and realtive speed to train the model.

3.5.2 Learning Rates Accuracy Results

Training Time	Learning Rate	Test Accuracy	Epochs	Optimiser
02:31:15	0.1	73.3%	140	SGD
02:32:52	0.01	81.01%	140	SGD
02:33:00	0.001	69.75%	140	SGD
02:33:22	0.0001	72.7%	140	SGD
02:33:39	0.00001	72.7%	140	SGD

The results presented above were evaluated on testing data and shows the direct relation of the time required to train convolutional neural network where decreasing learning rates requires more time to train models. These results are obtained by traing the model on Nvidia GTX-1080 gpu(graphical processing unit), training time might differ on different gpu based on it computational power.

3.5.3 Epochs Experiment

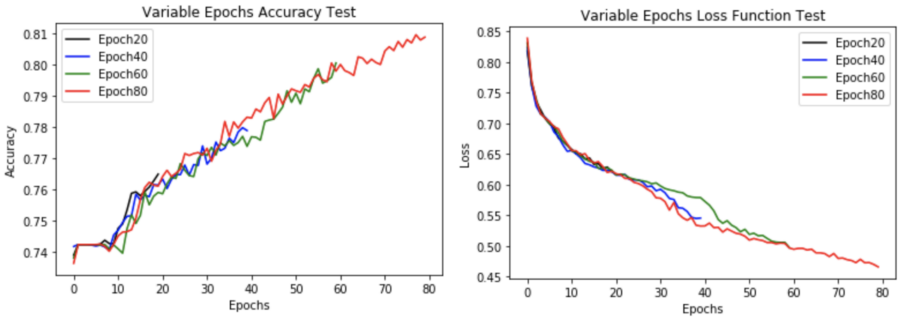


Figure 3.10: Results obtained different epochs

The figure 3.10 shows the accuracy of model with same architecture for different number of epochs. The model accuracy is directly proptional the number of epochs as training the nural networks is optimisation problem and objective is to find minimum of the cost function. The model accuracy on training data improves over each epoch as the model finds local minimum of cost function at each epoch and improve the predection in the next iteration. However, when the model reaches the gloabal minimum of the objective function there will be improvments in model accuracy. The figure 3.10 shows the model trained with the most number of epochs which is eighty in these experiments has least value of cost function and maximum training accuracy.

Learning Rate	Test Accuracy	Epochs	Optimiser
0.01	73.61%	20	SGD
0.01	76.97%	40	SGD
0.01	79.46%	60	SGD
0.01	78.68%	80	SGD

Chapter 4

Evaluations and Results

In this chapter, you should evaluate what you have done, and say what answer (to your research question) you have arrived at. It may be that in your method you describe some experiments, and this section records your results and analysis of those results. This is an important section – most students gain or lose marks in either their literature review or evaluation. The key to producing a convincing evaluation is to plan very early in the project what information or results you will need to write this section.

Chapter 5

Discussion

this is a discussion section

Chapter 6

Project Managment

6.1 Software Development Lifecycle

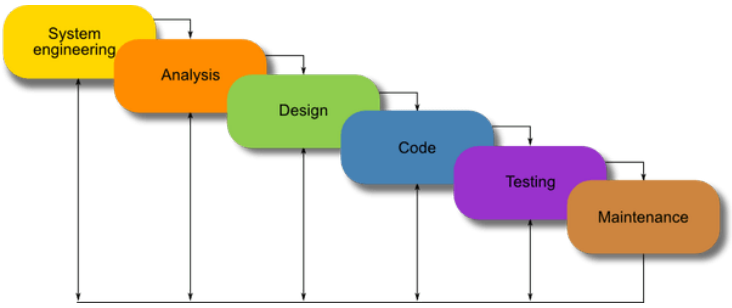


Figure 6.1: Waterfall Model

The waterfall software development lifecycle was used during developing the project. The waterfall model also known as linear-sequential life cycle model focuses on completing each phase of development before switching to the next stage of development Cite1. The waterfall model was accurate for this project as the scope of the project is small and was developed individually. Output from each phase of development lifecycle acts as the input to the next phase. The figure above 6.1 shows the various phases of the waterfall development lifecycle. In initial phase of the development the requirements and targeted audience were analysed as mentioned in the introduction section of the project. The second phase involved developing conceptual models using UML(Unified Modelling Language) to design the system using component diagram which captures the structural and sequence diagram to capture the behavioural design of the system. The next phase of waterfall model was implementation of the intelligent system to detect pigmented skin lesions. The implementation phase of the lifecycle involved developing convolutional network and performing various

experiments to get optimal performance. Furthermore, The next phase of development was to test the effectiveness of the overall system for which the prediction results gathered from medical professionals in the form of questionnaires were compared with the automated system and results were analysed with confusion matrix. The last phase was to deploy the model to the web-based system which was done by converting the keras model to json file and using tensorflowjs. At last, the maintenance phase of lifecycle cannot be applied to short term project.

6.2 Work Managment System

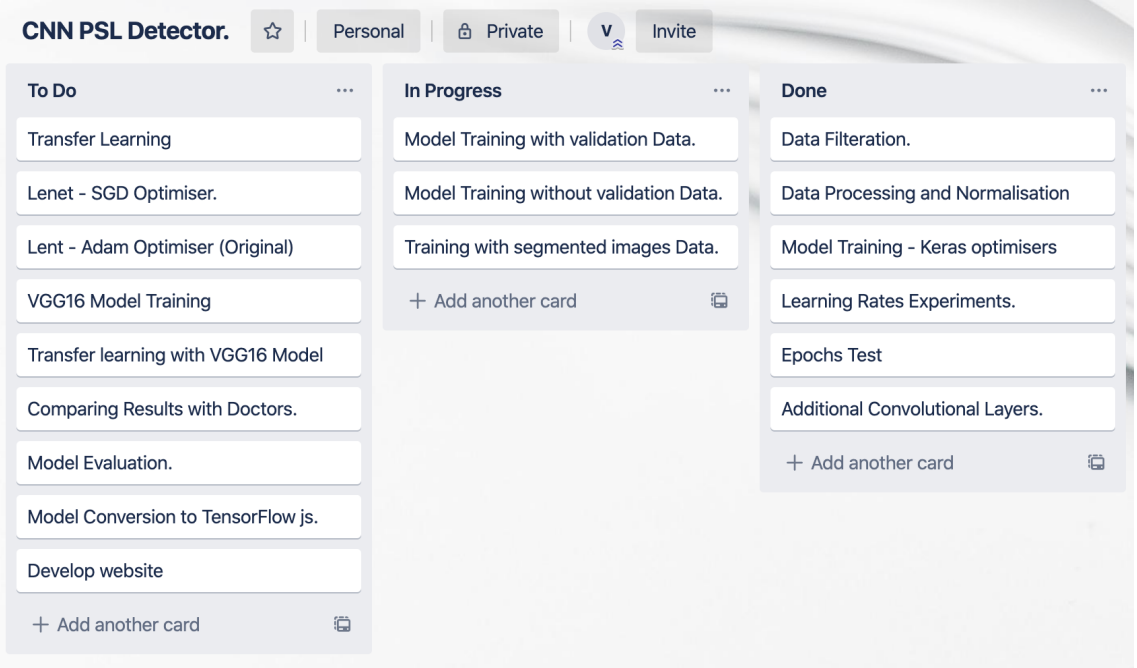


Figure 6.2: Kanban Board

6.3 Version Control

Chapter 7

Reflection

This is dummy text for reflection

Chapter 8

Conclusion

CONCLUSION is pending

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Appendices

Participant No.

INFORMED CONSENT FORM:

Convolutional Neural Network-based medical check-up system for Pigmented Skin Lesions Classification.

You are invited to take part in this research study for the purpose of collecting data on evaluating the reliability of automated skin check-up system for classification of common types of pigmented skin lesions.

Before you decide to take part, you must **read the accompanying Participant Information Sheet.**

Please do not hesitate to ask questions if anything is unclear or if you would like more information about any aspect of this research. It is important that you feel able to take the necessary time to decide whether or not you wish to take part.

If you are happy to participate, please confirm your consent by circling YES against each of the below statements and then signing and dating the form as participant.

1	**I confirm that I have read and understood the Participant Information Sheet for the above study and have had the opportunity to ask questions**	**YES**	**NO**
2	**I understand my participation is voluntary and that I am free to withdraw my data, without giving a reason, by contacting the lead researcher and the Research Support Office at any time until the date specified in the Participant Information Sheet**	**YES**	**NO**
3	**I have noted down my participant number (top left of this Consent Form) which may be required by the lead researcher if I wish to withdraw from the study**	**YES**	**NO**
4	**I understand that all the information I provide will be held securely and treated confidentially**	**YES**	**NO**
5	**I am happy for the information I provide to be used (anonymously) in academic papers and other formal research outputs**	**YES**	**NO**
6	**I am happy to answer questions asked in this questionnaire**	**YES**	**NO**
7	**I agree to take part in the above study**	**YES**	**NO**
Thank you for your participation in this study. Your help is very much appreciated.			

Participant's Name	**Date**	**Signature**
Researcher	**Date**	**Signature**

Consent form

Coventry University

Participation Information Sheet

Convolutional Neural Network-based medical check-up system for Pigmented Skin Lesions Classification.

PARTICIPANT INFORMATION SHEET

You are being invited to take part in research on developing a system for automated classification of common pigmented skin lesions for the general audience. Vinayak Sareen, BSc. Computer Science Student at Coventry University is leading this research. Before you decide to take part, it is important you understand why the research is being conducted and what it will involve. Please take time to read the following information carefully.

What is the purpose of the study?
The purpose of the study is to develop and investigate the reliability automated systems to classify the pigmented skin lesions which can be used by the general audience. The research will compare the classification results observed by medical professionals on pigmented skin lesions and the automated system to understand its reliability.

Why have I been chosen to take part?
You are invited to participate in this study because your input can contribute towards the research to investigate the overall reliability of the automated system for the classification of common pigmented skin lesions. The research will focus on investigating common categories of common pigmented skin lesions (melanoma, benign keratosis , melanocytic nevi, basal cell carcinoma).

What are the benefits of taking part?
By sharing your experiences with us, you will be helping Vinayak Sareen and Coventry University to better understand the medical performance of AI-based automated systems for common pigmented skin lesion detection. expectations of a medical professional from such an automated system and related concerns. Your data will be analysed and compared with the current performance of automated systems.

Are there any risks associated with taking part?
This study has been reviewed and approved through Coventry University's formal research ethics procedure. There are no significant risks associated with participation.

Do I have to take part?
No – it is entirely up to you. If you do decide to take part, please keep this Information Sheet and complete the Informed Consent Form to show that you understand your rights in relation to the research and that you are happy to participate. Please note down your participant number (which is on the Consent Form) and provide this to the lead researcher if you seek to withdraw from the study at a later date. You are free to withdraw your information from the project data set at any time until the data is destroyed on 17/04/2020 /until the data is fully anonymised in our records. You should note that your data may be used in the production of formal research outputs (e.g. journal articles, conference papers, theses and reports) prior to this date and so you are advised to contact the university at the earliest opportunity should you wish to withdraw from the study. To withdraw, please contact the lead researcher (contact details are provided below). Please also contact the Research Support Office [email esx072@coventry.ac.uk;] so that your request can be dealt with promptly in the event of the lead researcher's absence. You do not need to give a reason. A decision to withdraw, or not to take part, will not affect you in any way.

What will happen if I decide to take part?
You will be asked a number of questions regarding common pigmented skin lesions and it's current diagnostic methods. The questionnaire/interview/focus group will take place in a safe environment at a time that is convenient to you. Ideally, we would like to audio record your responses (and will require your consent for this), so the location should be in a fairly quiet area.