MELANOMA DETECTION

S02/ Group 3

Sng Yi Xuan (U2021009B)
Sydney Teo Wen Xuen (U2021555B)
Ivan Lua Yangzhi (U2022506F)
Cao Thuc Anh (U2010720G)
Teresa Zhang Han Yu (U2022886C)
Yam Hui Jing (U2021656A)

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PROBLEM STATEMENT

01

Melanoma

Melanoma is a type of skin cancer

- **Malignant** (tumor can grow and spread to other parts of the body)
- **Benign** (not cancerous by nature, but has risk to become cancerous)

Early Diagnosis & Treatment

As high as

99%

survival rate, if it is detected and treated early.

Difficult To Distinguish

It can be difficult to distinguish between normal mole, benign and malignant melanoma.

<u>Methods:</u>

1) Naked eyes
2) Screening test

Country with highest number of Melanoma cases

16,171

Cases in Australia in 2020

2 Main Stakeholders

HEALTHCARE INDUSTRY

1) Low diagnostic accuracy
2) Shortage of dermatologists

PUBLIC

1) No means for reliable self diagnosis
2) Lack of affordable screening
3) Long and tedious diagnosis procedure

2 Main Stakeholders

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Healthcare Industry

Low diagnostic accuracy

- Current practice of initial melanoma diagnosis is clinical and subjective.
    - Average diagnostic accuracy of 85% by trained expertise
- Limitations to dermoscopy

Healthcare Industry

Severe shortage of dermatologists

- Only 550 practicing dermatologists in Australia
    - Almost 15 percent less than what is required to meet the needs of the population
- Diagnostic accuracy is highly dependant on the trained expertise of dermatologists

2 Main Stakeholders

HEALTHCARE INDUSTRY

1) Low diagnostic accuracy
2) Shortage of dermatologists

PUBLIC

1) No means for reliable self diagnosis
2) Lack of affordable screening
3) Tedious diagnosis procedure

Public

No means to conduct reliable diagnosis

- Diminishes the chances for the public for early detection
- Detection of melanoma in Australia is mainly by chance

Public

Lack of affordable screening

- Cost for skin cancer in Australia ranges from AU $644 to AU $100,725
  - Minor biopsy: $90 - 120
  - Standard/excision biopsy: $160 - 240
  - Full body skin cancer check: $120
  - Full body skin cancer check + mole mapping :$170

Public

Long and tedious diagnosis procedure

- Appointment to do a screening evaluation of their melanoma condition
- Long waiting time (2-3 weeks) to obtain biopsy results

OPPORTUNITIES

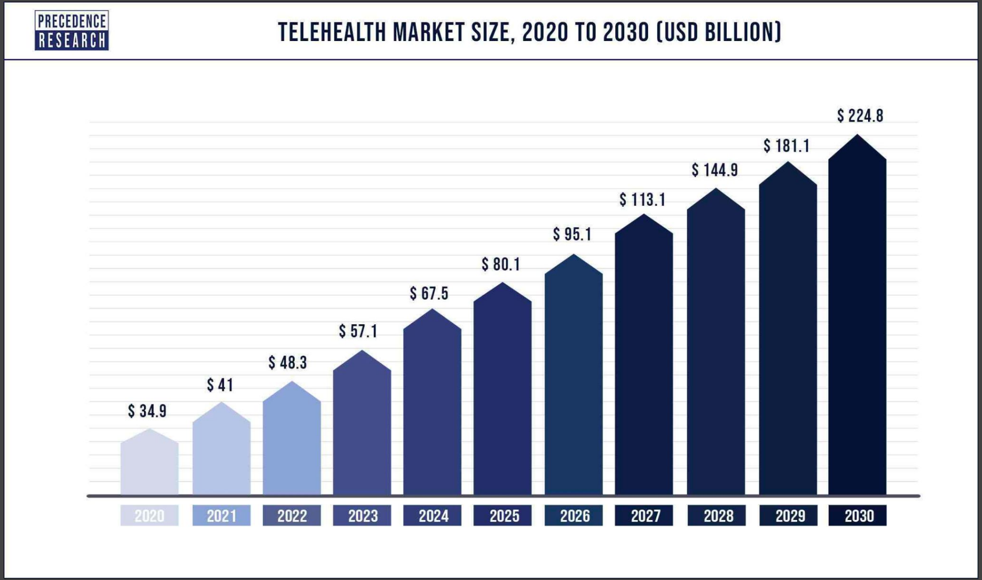
02

Telehealth Market

Telehealth is a growing market

- The rising penetration of the internet has made telehealth services faster and convenient
- The demand for telehealth services is growing due to the COVID-19 restrictions

The Global Telehealth Market



$41b

In 2021

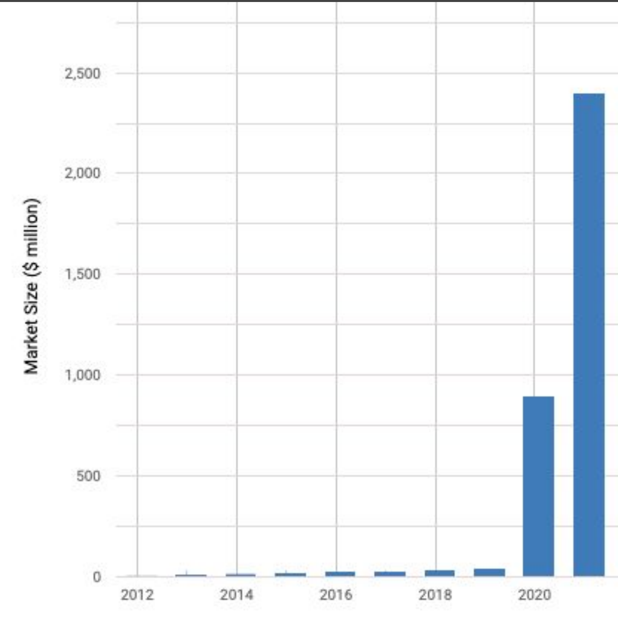
$224.8b

Expected in 2030

18.8% per year

Between 2022-2030

The Australia Telehealth Market



$103.1m

In 2022

26.4% per year

Between 2017-2022

Line Average Pooling: A Better Way to Handle Feature Maps on CNN for Skin Cancer Classification

Chen Zipei
Electrical and Electronic Engineering
University of Electronic Science and Technology of China
Chengdu, China
1728110154@qq.com

Du Yifei
Electrical and Electronic Engineering
University of Electronic Science and Technology of China
Chengdu, China
1506407889@qq.com

Teoh Teik Toe
NTU Business AI Lab
Nanyang Technological University
Singapore
ttteoh@ntu.edu.sg

***Abstract*—This paper proposes a new pooling method called line average pooling (LAP), which operates between the convolution layer and the final output layer, replacing the traditional mapping method, such as Flatten and global average pooling (GAP). LAP effectively reduces the total number of parameters of the model, thereby preventing overfitting effectively while retaining more features from high-level feature maps. Additionally, it increases the fitting speed of the model. We selected the ISIC skin cancer dataset, then examined the performances of three pooling methods: LAP, GAP and Flatten, on a customized CNN model. In addition, we analyzed the fitting degree when the epoch was 100. The experimental results show that, the degree of overfitting using LAP is greatly reduced when compared with Flatten, reaching 83.12% on the test set. Compared with GAP, LAP is better and faster in extracting features and fitting the training data. Both GAP and LAP demonstrate good generalization abilities, reaching 87.56% and 88.11% respectively. With proper means of additional regularization, LAP can even preform better than GAP.**

Keywords—Image classification, CNN, pooling, average, overfitting.

I. Introduction

As a branch of machine learning, deep learning has developed rapidly in the past two decades. The reason is that a series of neural networks with large parameters and complex structures have been established, which can be used to widely extract the characteristics of input information, thereby dividing the decision boundary more accurately. In the neural network, the convolutional neural network (CNN) is a classical and efficient network hierarchy. CNN was first proposed by Yann Lecun and applied to handwritten number recognition [1]. Its essence is a multi-layer perceptron. The reason for its success lies in the way of local connection and weight sharing, enabling effective feature extraction on images at different scales.

CNN has a very wide range of applications in a series of fields such as image recognition, lesion detection and feature analysis [2]. It is intensively used in medical field for lesion classification purpose [3]. The network structure of CNN mainly includes: convolutional layer, down sampling layer and fully connected layer.

The pooling operation is generally conducted after the convolution layer, and its objective is to reduce the amount of data processing while retaining useful information, thus making the network have better generalization ability [4]. As network continues to deepen, parameters which require updating increase enormously. Some redundant parameters occur and they can be trained on unwanted or incorrect features, leading to common overfitting problems. In addition, a Flatten operation is commonly used in the transition from the convolutional layer to the fully connected layer, which could "flatten" the input, that is, to make the multi-dimensional input become one-dimensional [5]. Therefore, the problem of overfitting became much more severe in CNN. To prevent overfitting, a global average pooling (GAP) method was proposed in *Network in Network* in 2014, by Min Lin et al. [6]. GAP is widely used in many classical multi-layer CNN networks, such as ResNet, ShuffleNet, and DenseNet. In a common convolutional neural network, the convolutional layer

CURRENT RESEARCH

Line Average Pooling (LAP), a new pooling method:

- Retain more high-level feature maps, reduce training time.
- Reduce overfitting (~81.32%)

Telehealth Market will be profitable

Competitor Analysis - Overview

66 apps commercially downloadable for consumers in 2019

49% artificial intelligence image lesion analysis

39% aimed at supporting monitoring and tracking of lesions

38% education provision

27% teledermatology services

Competitor Analysis

	miiskin	MoleScope by MetaOptima	SkinVision
Diagnosis?	No	No	Yes, accuracy of 95%
Features	Skin check/tracking app without diagnosis	Hardware skin magnifier (imaging, archiving, communication)	Self-examine, regulated medical service
Price	$2.31 - 5.28/month	$49.99 - 299	$6.99 - 49.99 (check times)
Downloads	100K+ (Play Store)	10K+ (Play Store)	500K+ (Play Store)
Markets	Europe, America	Global	Global
USP	Mole Sizing (AR)	Portable skin viewer	Highly accurate diagnosis (~95%)

Competitor Analysis

- The competitors charge a certain amount to utilise premium features
- SkinVision is our closest competitor since it is also using Artificial Intelligence. It has a high accuracy and has a large consumer base with a strong brand image.
- This motivates us to take advantage of advanced technology to create a more affordable melanoma therapeutics solution for a better community health, to create a free-of-charge application that is accessible to even those of low-income.

Our Stand

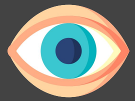
As a new market entrant, understanding the danger of melanoma and the importance of early detection, our team desire to bring an economical, easy-to-use technology-driven solution that can help people check skin anomaly at their convenience with just a single click on their phones, which facilitate possible early treatment and create a healthy community.

PROJECT OBJECTIVES & GOALS

03

Main Objective

Current Methods

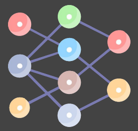


Naked Eyes

Screening Test

Addresses limitations

Additional Method



CNN

Early detection of Melanoma → **Reduce mortality rate for patients with Melanoma**

Healthcare Industry

Problem

1) Low diagnostic accuracy
2) Shortage of dermatologists

Solution

1) Train a CNN model that is accurate
2) Tools and features in the front-end that can help the dermatologists

Public

Problem

1) No means for reliable self diagnosis
2) Lack of affordable screening
3) Tedious diagnosis procedure

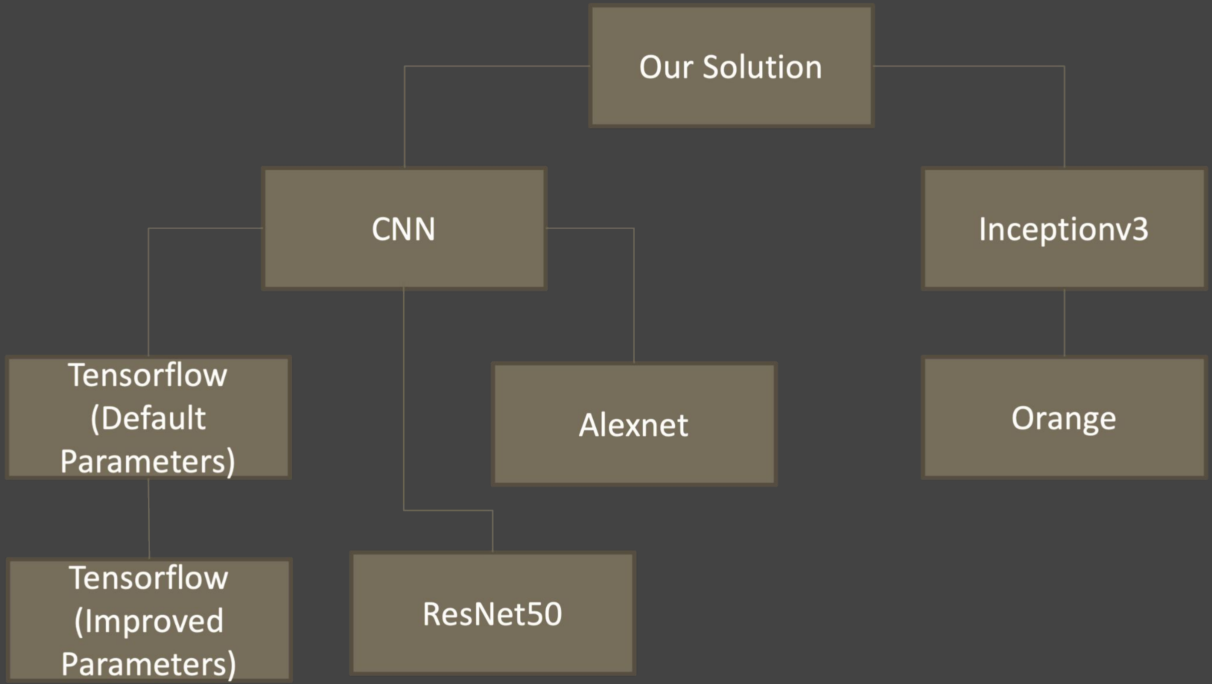
Solution

1) Train a CNN model that is accurate
2) Free and highly accessible front-end
3) Convenient product

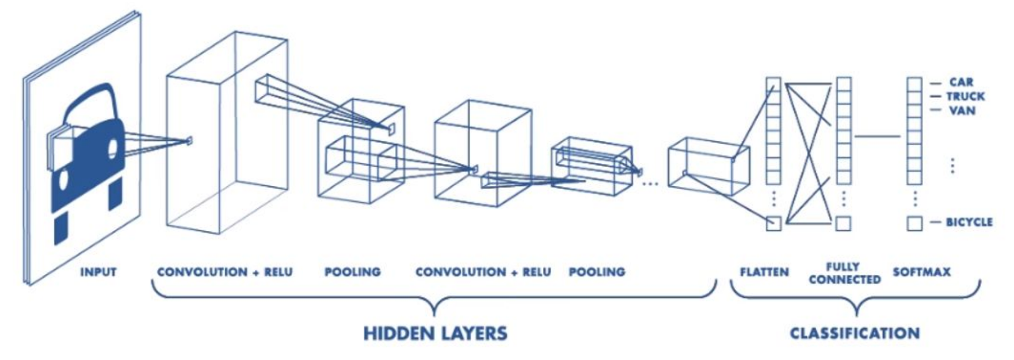
OUR SOLUTIONS

04

Overall Approach



CNN Architecture



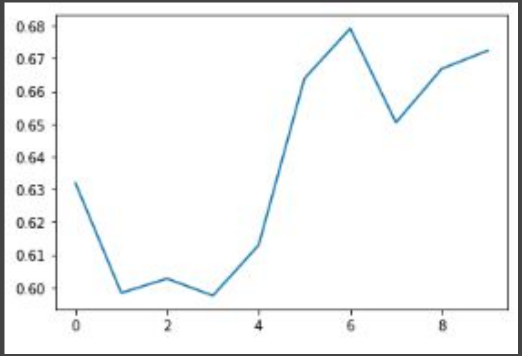
4 Main Layers

1) Convolution Layer
2) ReLU (Rectified linear unit) activation layer
3) Pooling Layer
4) Fully Connected Layer

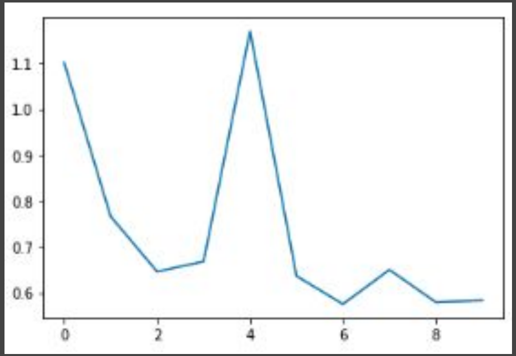
Default Parameters

- 4 Convolution Layers
- Input_shape = (150, 150, 3)
- Filter size = (3x3)
- Number of filters for each layer = (32, 32, 64, 64)
- MaxPool = (2,2) with stride 2
- Softmax activation function

Initial Approach - Tensorflow (Default Parameters)



Model Accuracy



Model Loss

	Accuracy	False Negative Rate	Precision	Recall
Result	0.694	0.610	0.995	0.390

Data Augmentation

1. Rescalling

Scaling the image ensures object is recognized by the network regardless of how zoomed in or out the image is.
[1. / 255]

2. Zoom Range

Zoom augmentation randomly zooms the image in and either adds new pixel values around the image or interpolates pixel values respectively
[zoom_range=0.2]

3. Rotation

Rotation helps the models not consider the angles of an image to be a distinct feature for prediction
[rotation_range=15]

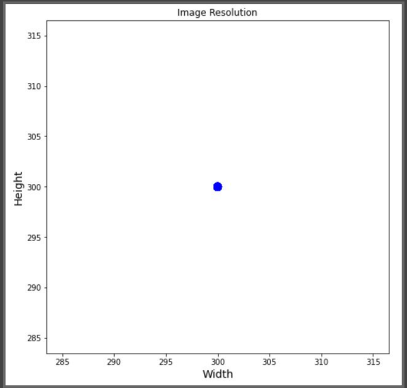
4. Flip

Through Flipping images, the optimizer will not become biased that particular features of an image are only on one side
[horizontal_flip=True]

Deciding the Best Parameters

Train Benign Dataset
Total Nr of Images in the dataset: 5000

	FileName	Size	Width	Height	Aspect Ratio
0	melanoma_0.jpg	(300, 300)	300	300	1.0
1	melanoma_1.jpg	(300, 300)	300	300	1.0
2	melanoma_10.jpg	(300, 300)	300	300	1.0
3	melanoma_100.jpg	(300, 300)	300	300	1.0
4	melanoma_1000.jpg	(300, 300)	300	300	1.0



Convolution Layer

1. **Use 3 layers instead of 4**
   - After 2-3 layers, accuracy gain becomes small
   - Reduce complexity of the model with fewer layers
   - Reasonable training time
2. **Image size used input_shape (300,300,3) instead of (150,150,3)**
   - Downscaling bigger will make it harder for CNN to learn the features
   - Upscaling causes small images to be upscaled and padded with zero
   - Important to obtain ideal image size
3. **Default filter size 3x3**
4. **Number of filters for each layer = (32, 64, 128)**

Deciding the Best Parameters

```
nb_fc_neurons = 512

model.add(Flatten())
model.add(Dense(nb_fc_neurons))
model.add(Activation('relu'))
model.add(Dropout(0.5))

model.add(Dense(1))
model.add(Activation('sigmoid'))
```

```
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

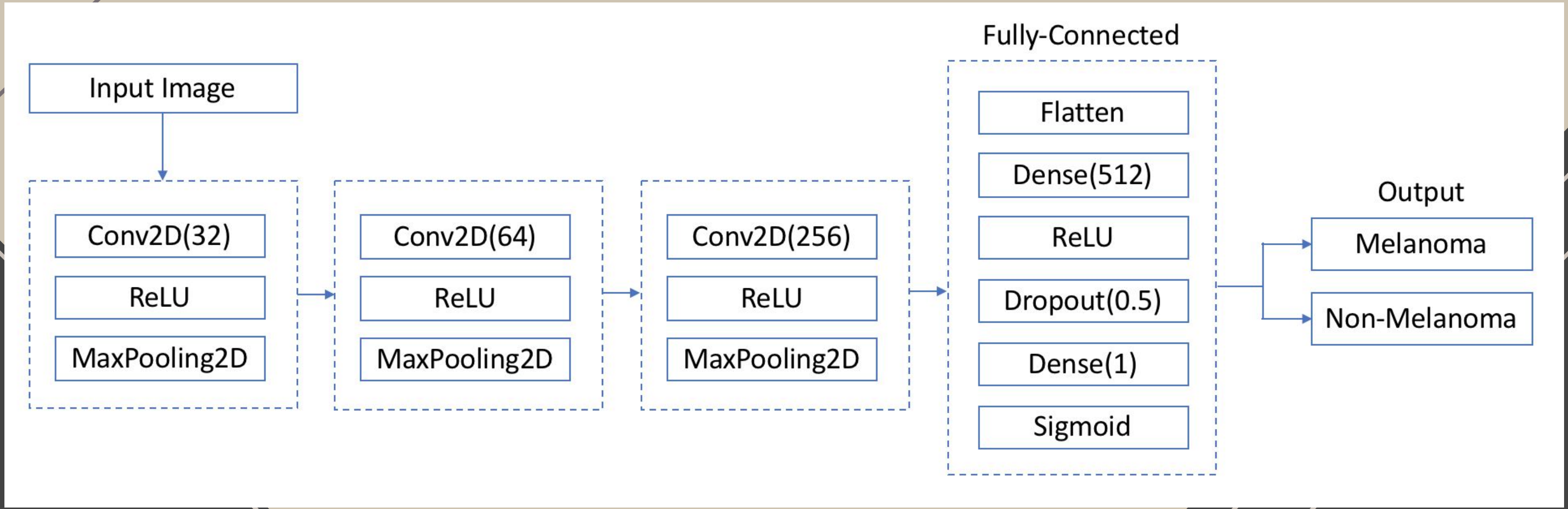
Pooling Layer

1. **MaxPool size 2x2 with a stride of 2**

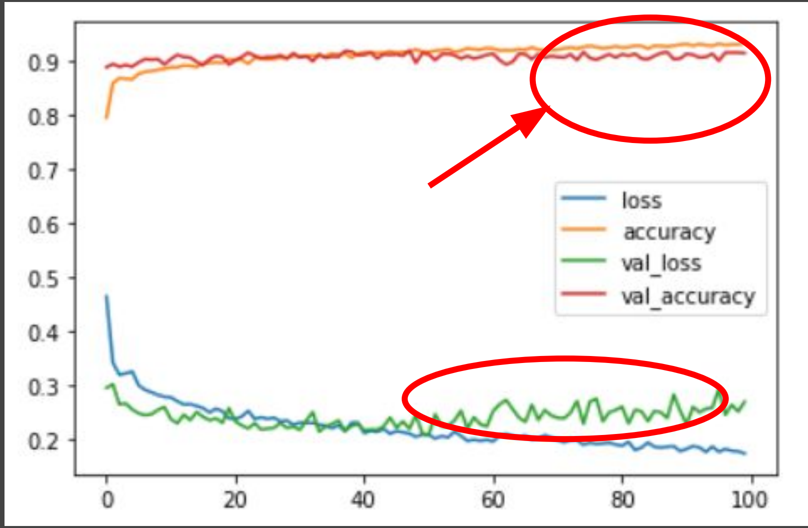
Fully Connected Layer

1. **512 number of neurons with 1 hidden layer**
   - Faster training and better accuracy
2. **Dropout = 0.5**
   - Prevent overfitting
3. **Activation function sigmoid**
   - Suitable for binary output
   - Malignant (1) and Benign (0)
4. **Binary cross entropy as loss function**
5. **Batch size 16 instead of 5**

Tensorflow Architecture Block Diagram



Results for Improved Model



	Accuracy	False Negative Rate	Precision	Recall
Result	0.913	0.114	0.937	0.886

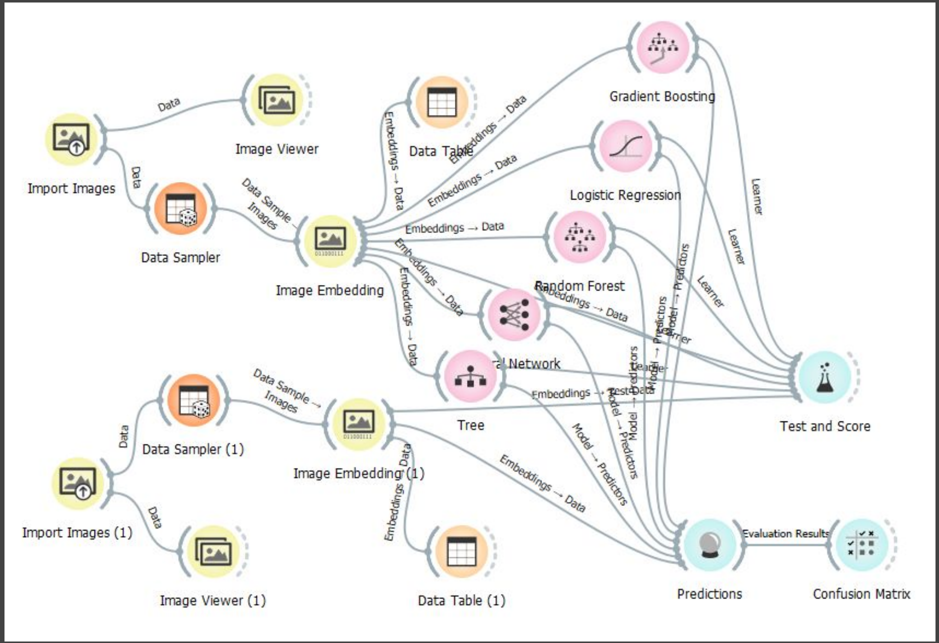
OTHER MODELS

05

InceptionV3 (Orange)

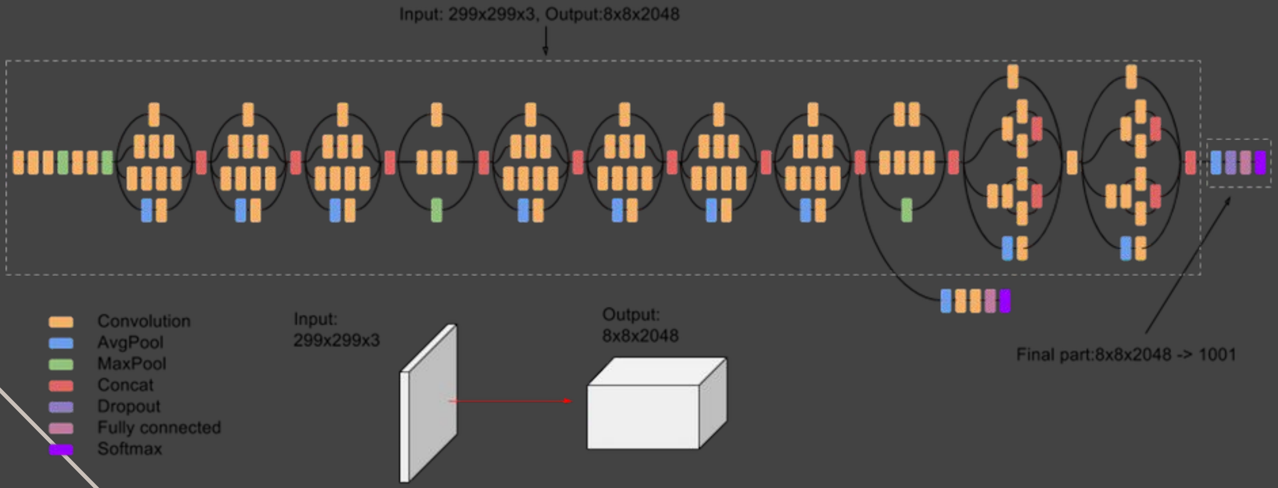
Orange

- An open-source data visualization, machine learning and data mining toolkit.
- Functions: Compare learning algorithm, visualise data elements

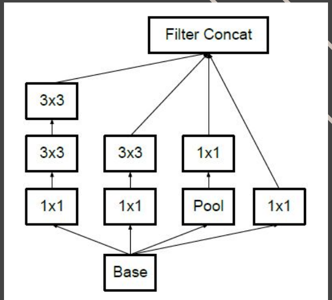


InceptionV3

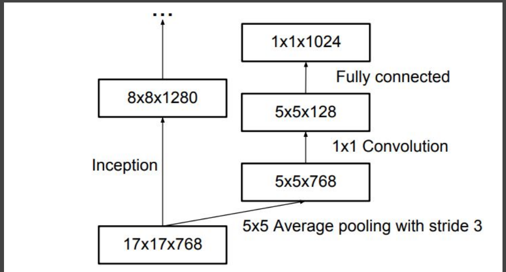
- More advanced model of InceptionV1
- 42 layers
- 78.1% accuracy on ImageNet dataset.
- Elements: Symmetric block, Asymmetric block, Auxiliary classifier



Full architecture



An Inceptionv3 module



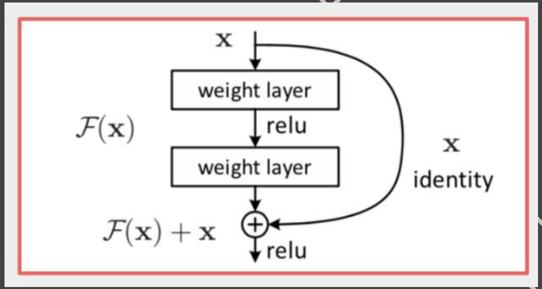
Auxiliary classifier

Inceptionv3 - Result

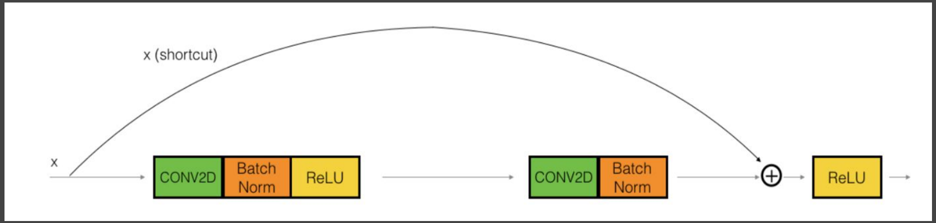
Model	AUC	CA	F1	Precision	Recall
Tree	0.828	0.857	0.857	0.857	0.857
Random Forest	0.952	0.884	0.884	0.884	0.884
Neural Network	0.966	0.907	0.907	0.909	0.907
Logistic Regression	0.960	0.897	0.897	0.897	0.897
Gradient Boosting	0.961	0.905	0.905	0.906	0.905

ResNet-50

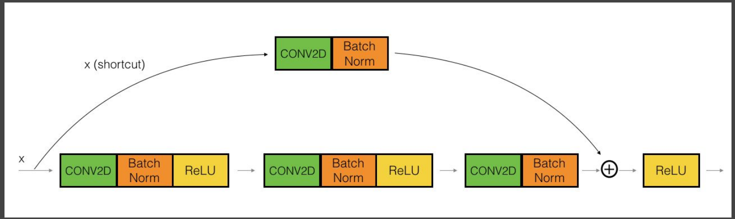
ResNet-50



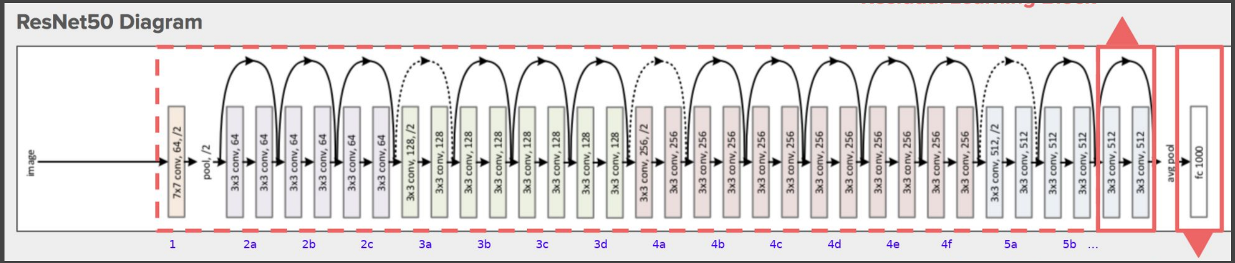
- Residual Network - 50 layers
- Identity mapping - skip connections
- Elements:



Identity block



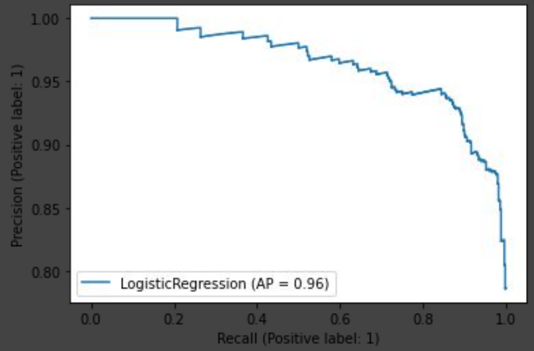
Convolutional block

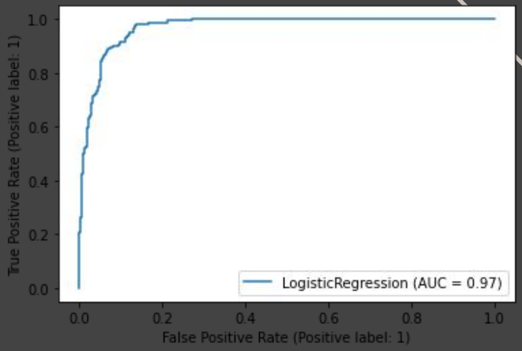


Full architecture

ResNet-50 - Result

- Accuracy: 91.4%
- FNR: 5.2%
- Precision: 96.7%
- Recall: 90.7%





AlexNet

What is AlexNet?

AlexNet is the name of a convolutional neural network (CNN) architecture, designed by Alex Krizhevsky

WHY?

Competed in the ImageNet Large Scale Visual Recognition Challenge on September 30, 2012. The network achieved a **top-5 error of 15.3%**, more than 10.8 percentage points lower than that of the runner up

Why AlexNet?

01 ReLU Nonlinearity

ReLU's has low training time and was able to reach 25% error on CIFAR-10 dataset 6 times faster

02 Multiple GPUs

AlexNet allows for multi-GPU training and hence cuts down on training time

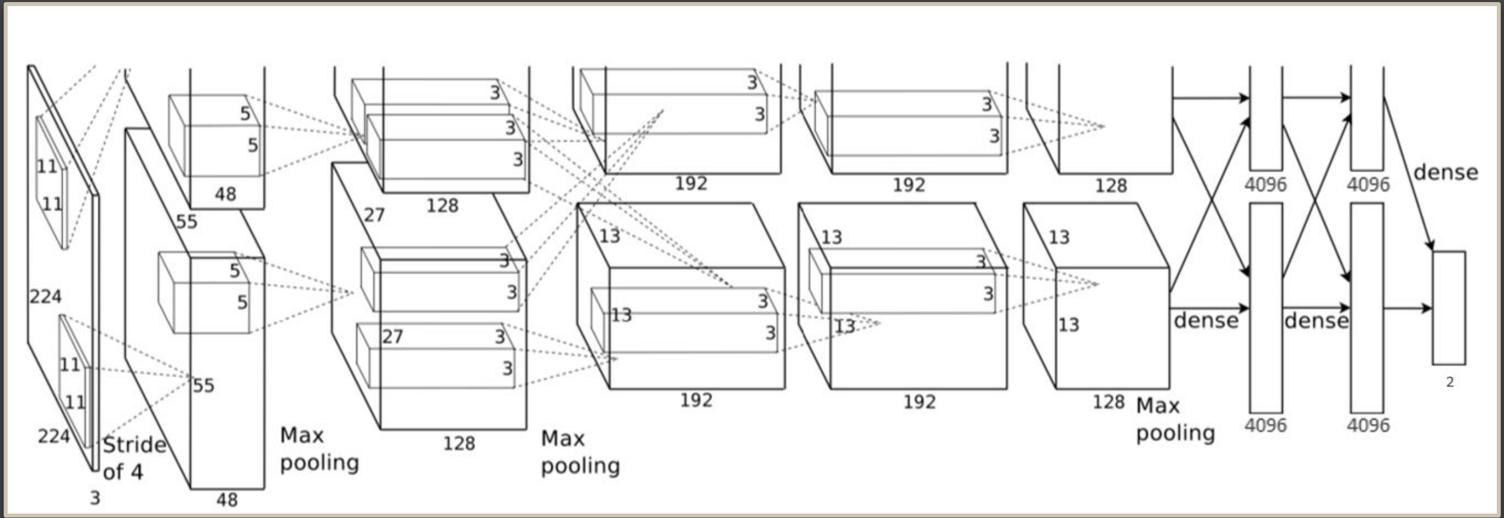
03 Overlapping Pooling

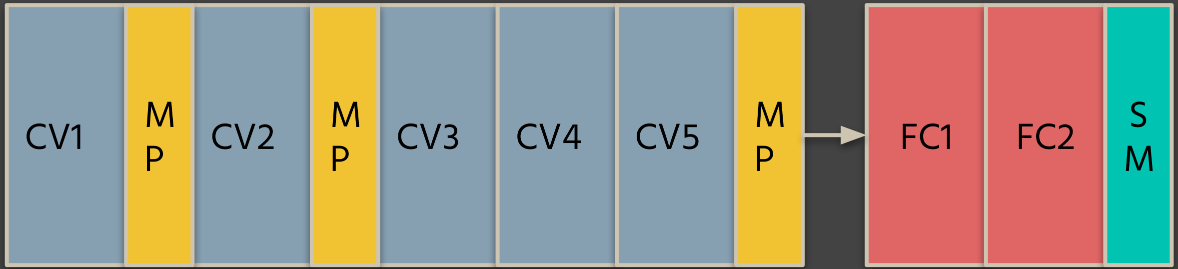
With overlapped pooling, there was a reduction in error by 0.5% which reduced overfitting

04 Dropout

Uses a predetermined probability to 'turn' off neurons which forces neuron to have more robust features

AlexNet Architecture





AlexNet Layers

5 Convolutional Layers

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	227x227x3	-	-	-
1	Convolution	96	55x55x96	11x11	4	ReLU
	MaxPooling	96	27x27x256	3x3	2	ReLU
2	Convolution	256	27x27x256	5x5	1	ReLU
	MaxPooling	256	13x13x256	3x3	2	ReLU
3	Convolution	384	13x13x384	3x3	1	ReLU
4	Convolution	384	13x13x384	3x3	1	ReLU
5	Convolution	256	13x13x256	3x3	1	ReLU
	MaxPooling	256	6x6x256	3x3	2	ReLU

AlexNet Layers

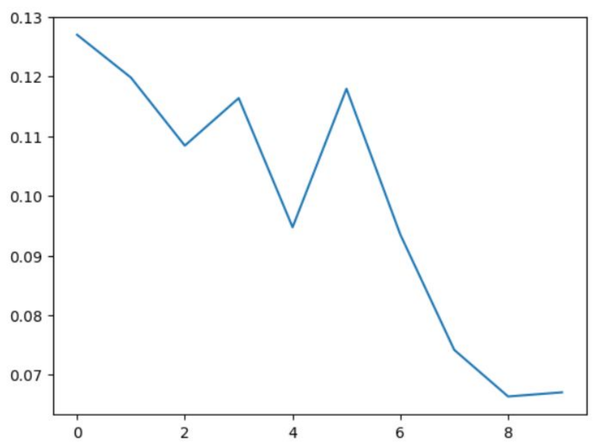
3 Fully-Connected Layers

Layer		Feature Map	Size	Kernel Size	Stride	Activation
	MaxPooling	256	6x6x256	3x3	2	ReLU
6	FC	-	4096	-	-	ReLU
7	FC	-	4096	-	-	ReLU
Output	FC	-	2			ReLU

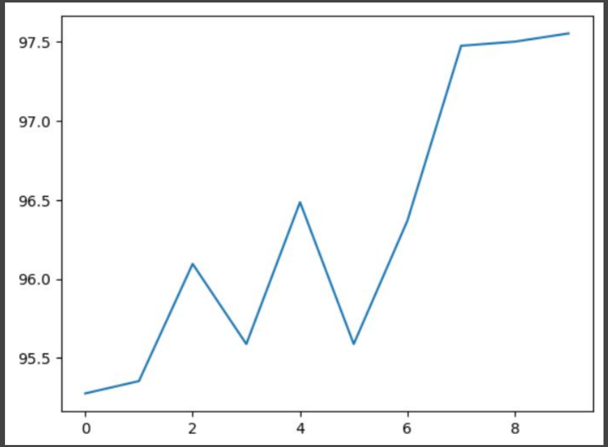
Training:

- 10 Epochs
- Batch Size 64
- K-fold cross-validation (K = 5)

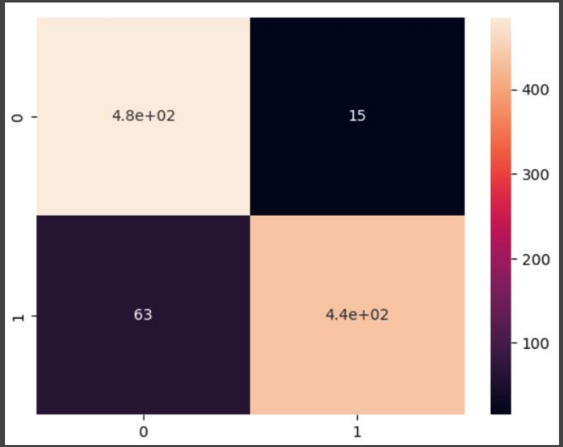
AlexNet Results



Loss Graph



Accuracy Graph



Confusion Matrix

Highest Accuracy
Highest Precision

	Accuracy	False Negative Rate	Precision	Recall
Result	**0.922**	0.126	**0.967**	0.874

ANALYSIS & EVALUATION

05

Key Performance Metrics

High Accuracy

Accuracy is the most important metric use to evaluate the effectiveness of classification problems. Evaluates the overall predictive power of a model

Low FNR

Low false negative is extremely important in the healthcare sector because we do not want to wrongly predict a patient to not have cancer when in actuality he has cancer

High Recall

To ensure that for all the patients that actually have malignant melanoma, they are not missed out in the prediction because the cost of not treating a patient that has cancer is potential a lost of a life

Choice of Model

"On average, human dermatologists accurately detected **86.6%** of skin cancers from images" - the Guardian

	Accuracy	FNR	Precision	Recall
TensorFlow Default Model	0.694	0.610	0.990	0.390
TensorFlow Improved Model	0.913	0.114	0.937	0.886
Orange	0.907	0.093	0.909	0.907
ResNet50	0.914	**0.052**	0.890	**0.948**
AlexNet-Based	**0.922**	0.126	**0.967**	0.874

BUSINESS IMPLEMENTATION

06

Novelty of our Application

Easy to Self-Diagnose

Importance of Early Diagnosis

Our Machine-Learning Application

Simplistic, intuitive and user-friendly

true health™

Powered By:

ResNet-50

Pre-Trained Model

Value-added Features

Smart

ResNet50 model provides better diagnosis accuracy than a professional dermatologist

Simple

Get a diagnosis with less than 20 seconds via our simple 3-stage process

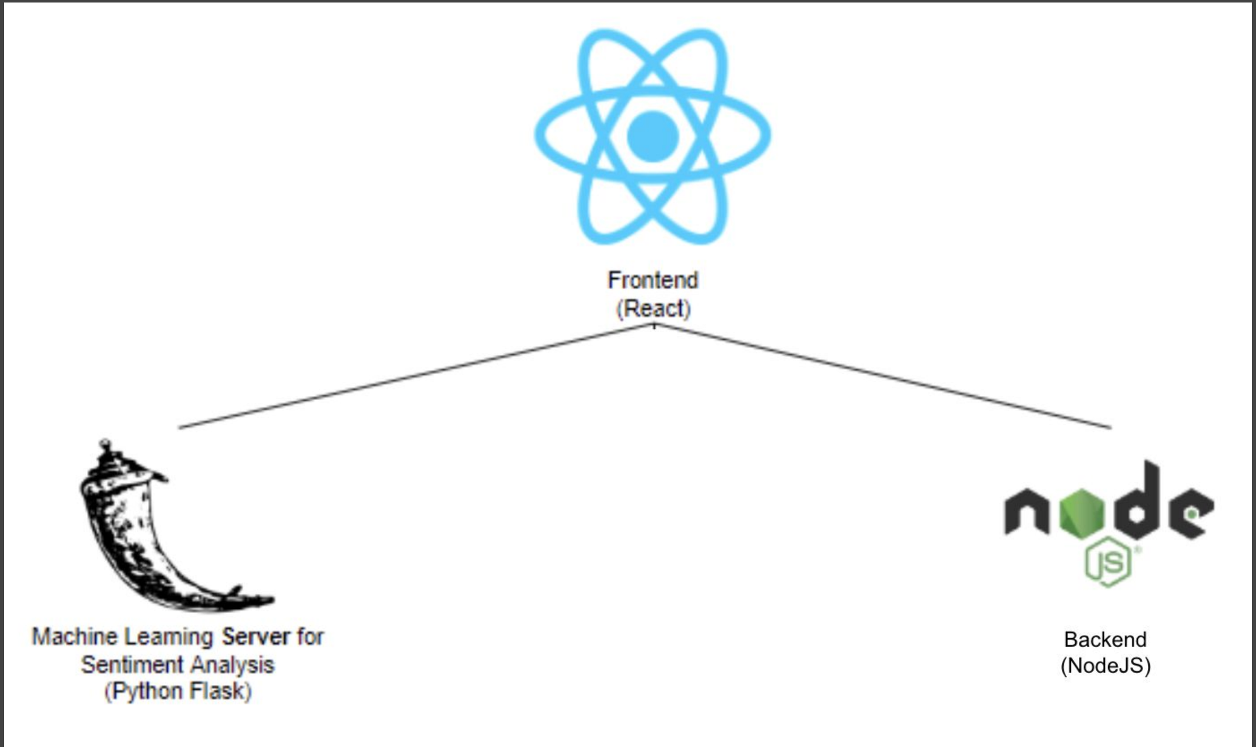
Accessible

TrueHealth is available anytime, anywhere. Keep your health in check at your fingertips even when you are on the go.

Free

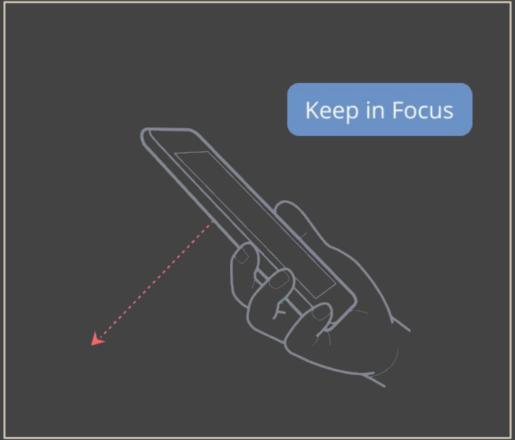
TrueHealth's leading image analytics features costs nothing, saving both time and money.

Technology Stack Architecture



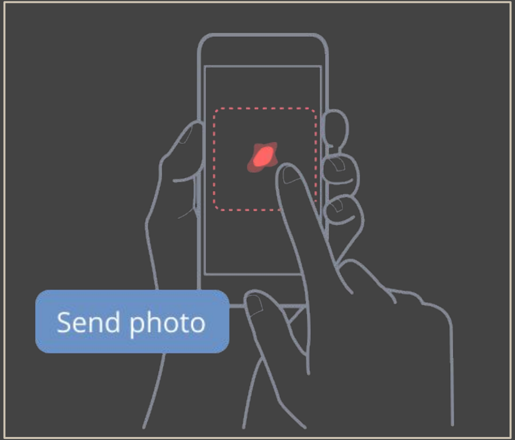
How to use TrueHealth?

Our 3-step process



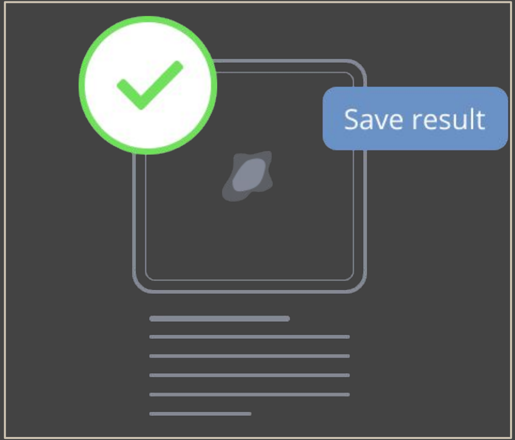
1 STEP

Take photo of area of concern



2 STEP

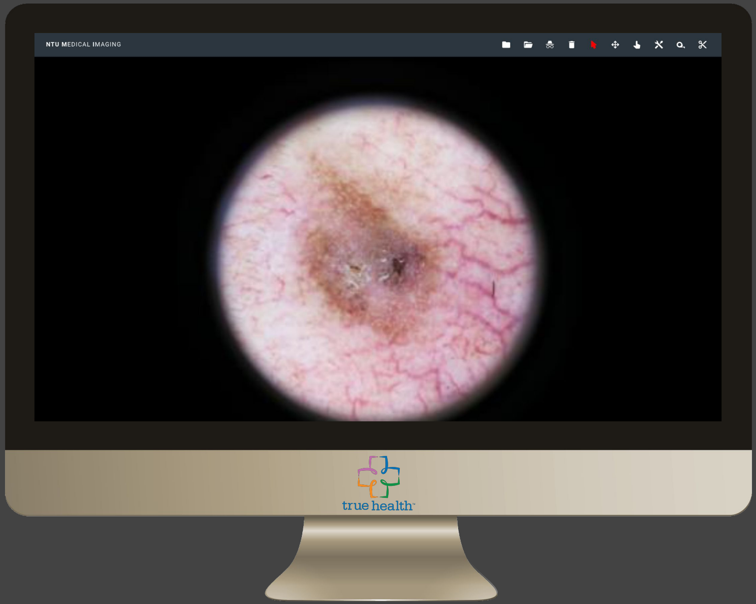
Upload and Diagnose



3 STEP

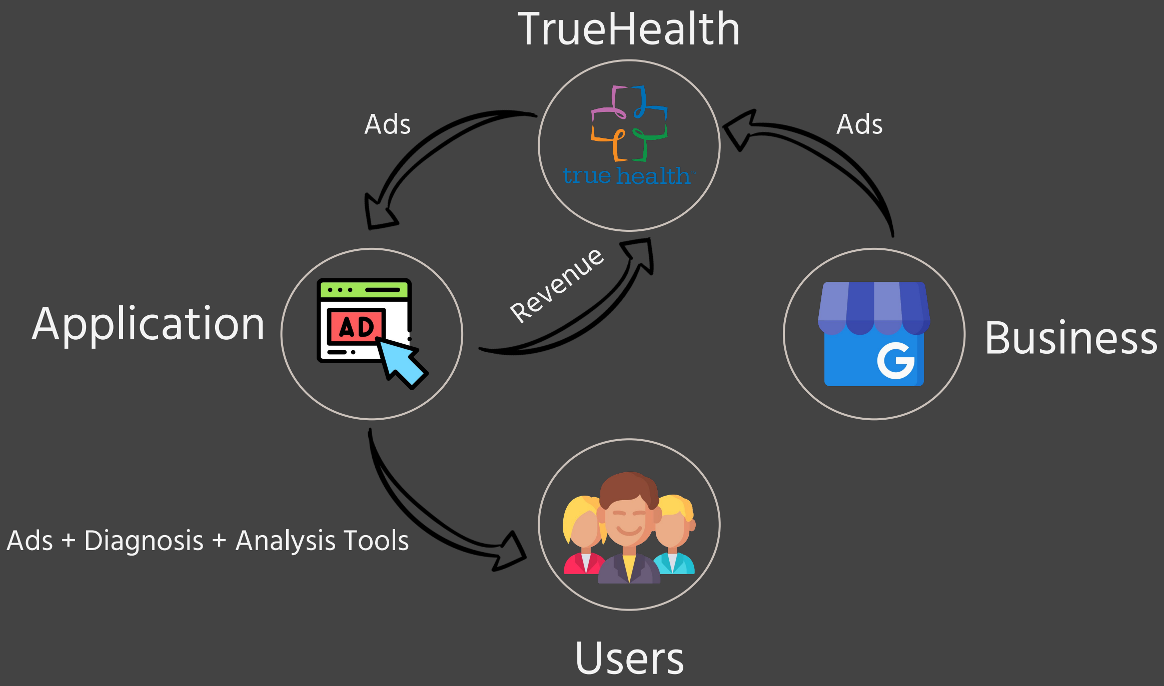
Retrieve result and Analyse

Application Demo



Business Model

Advertising-Based



EVALUATION

07

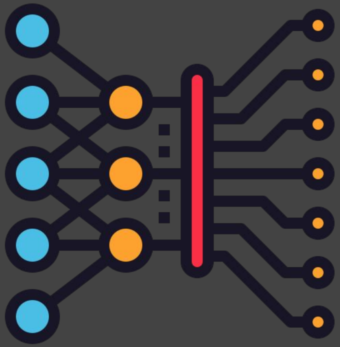
Limitations

Accuracy of Diagnosis

1. Not as accurate as market competitors
2. Less data and specialised equipment to produce better machine learning model

Sustainability of Application

1. Inability to handle large traffic due to business model due to higher costs



Limitation of ML models

1. Require pure, unbalanced and large datasets
2. Difficulty classifying image with different positions
3. Rare utilisation of Ugly Duckling recognition method
4. Slow speed of training

Future Plans

Stage 1

Other skin conditions

DermatoFibroma

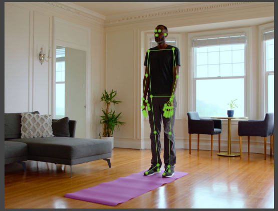
Stage 2

Beyond the skin

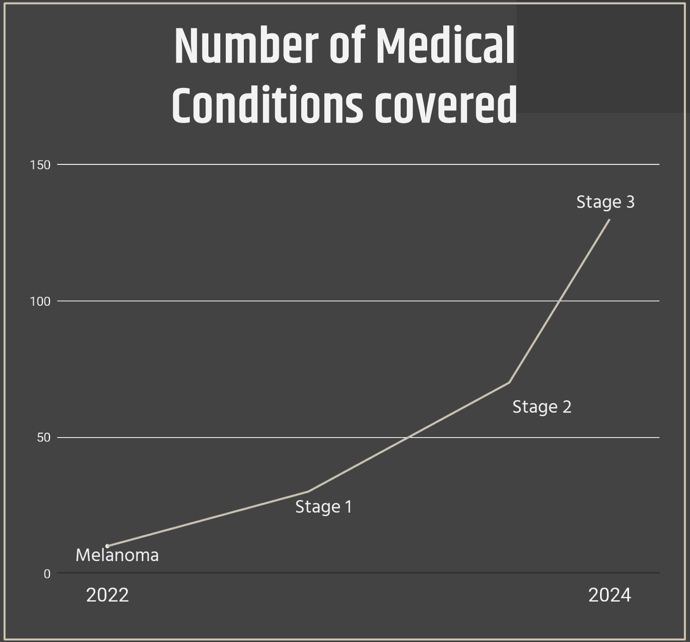
Cataract

Stage 3

Beyond inputs of images



Musculoskeletal (Computer Vision Technology)



Conclusion

true health™

Powered By:

ResNet-50

Pre-Trained Model