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Max Pooling Technique to Detect and Classify Medical Image for Ovarian Cancer Diagnosis

Booma P M [1], Vinesh Thiruchelvam [2], Julius Ting Seaa Ho [3]
[1,2,3] *Asia Pacific University of Technology & Innovation*
Technology Park Malaysia, 57000 Bukit Jalil, Kuala Lumpur

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Abstract:
Machine Learning plays a vital role in the field of Image classification. Researcher's originate image classification is one of the complex process. As well as researcher's strongly consider, the possibility of health screening using machine learning is massive and without compromising technical industries and professional healthcare bodies should compose to create an efficient healthcare screening system. Recently, reduction in the production of medicine and drugs, contribution of health screening in identifying diseases by Artificial Intelligence (AI) is essential. Considering various diseases, ovarian cancer is highly rated among women's. Production of Ovum and hormones is usually done by reproductive organs. As per statistics, patient have nearly 93% high chance to survive if diseases detected during preliminary stage. Conversely, early stage diagnosis hits only 20% due to less accuracy methods. By using Machine Learning identity patterns, detection of ovarian cancer in preliminary stages can be performed in more accurate detected without the guidance of doctors. This paper, introduces the methodology known as Enhanced Max Pooling (EMP) for detecting and classifying an ovarian cancer using advanced machine learning techniques. This methodology discusses the possibilities of using machine learning in the image classification and limitations to overcome.

Keywords:*Machine Learning, Image Classification, health screening.*

1. INTRODUCTION

With current techniques in market, preliminary detection of ovarian cancer is unsatisfactory as well as involves uncountable insight on diagnosis methods. According to statistics in 2011 by National Cancer Registry of Malaysia, it was evidenced that among 714 ovarian cancer cases, nearly 56% cases were diagnosed with final stage. Similarly a report by American Cancer Society in 2018, around 80% diagnosis of ovarian cancer patients done in critical and late stage.

Google has entered the healthcare screening field using CNN and has proven successful. Their findings shows that usage of machine learning techniques in assisting doctors for an early detection of prostate as well as breast cancers. According to Wiggers, Google DeepMind has developed a CNN which claimed to be have an accuracy of 99% in breast cancer metastases identification in lymph nodes, compared to pathologist with the accuracy of 62% (Wiggers, 2018). Google combined image recognition and a microscope to process video of biopsies. This microscope allows the machine learning model to identify and highlight cancer cells in real time (Stumpe, 2018). The research done by Kaymaka S. et al. agrees with the advancements of machine learning done by Google DeepMind, with an accuracy of 70.4% using radial basis neural networks (RBFN). This shows that a well-trained CNN can yield reasonable results compared to experienced pathologists in identifying one type of cancer.

Besides that, Esteva et al. concluded that Deep Convolutional Neural Networks (CNN) has been used in detecting Skin cancer by classifying skin lesions despite of using traditional diagnosis methods such as visual, dermoscopic analysis, biopsy and histopathological examination. The CNN in this study has been well trained with complete data in the form of image, with the help of only pixels and disease labels as input. The overall accuracy of the CNN has achieved 55.4% whereas the two dermatologists participated in the study achieved an overall accuracy of 53.3% and 55% each. This has shown that a well-trained CNN can achieve almost the same or more accuracy when compared to well-trained dermatologist or even better in some cases.

The proposed research aims to contribute a standard analytical system which has the capability to disrupt the healthcare industry by accurately diagnosing one disease at a time. While medicine is limited by the discovery of drugs and procedures, healthcare screening will enter a new stage where diseases are detected by artificial intelligence.

2. METHODOLOGY

Convolutional neural network (CNN) is the best performing machine learning technique when using supervised learning, as of 2018. CNN was developed by Yann LeCun in 1998. It achieved 99% accuracy for handwritten numbers, outperforming every other type of machine learning techniques. In 2012, Alex Krizhevsky used CNN to win the ImageNet Large Scale Visual Recognition Challenge by a margin of 10.5% less errors than the runner up, with only 15.3% top 5 error rating.

The CNN is made up of 3 convolutional blocks, trailed with fully connected layer. The CNN will ingest the image and convert it into a 2D array of 1 and 0 values. A filter consisting of a 2D array of numbers called weights acts as the feature identifiers. These weights are trained using back propagation, identifying patterns within an image. The image array will be multiplied by the filter to predict if the ovary in the image is healthy.

The methodology for the proposed research study encompass of 8 phases as follows:

1. Image collection of ovaries with and without cancer and label them accordingly
2. Pre-processing the collected image
3. Dataset of images will be split into 80% and 20% for training and testing respectively
4. CNN will be made out of 3 convolutional blocks of different filter sizes
5. Training Convoluted Neural Network (CNN) is performed with the help of Images
6. CNN model will be tested to determine the accuracy
7. Fine tuning of the CNN parameters, by applying various parameters and filters to improve accuracy
8. Further research will be conducted to determine if more layers will affect the accuracy of ovarian cancer identification

Structure of CNN

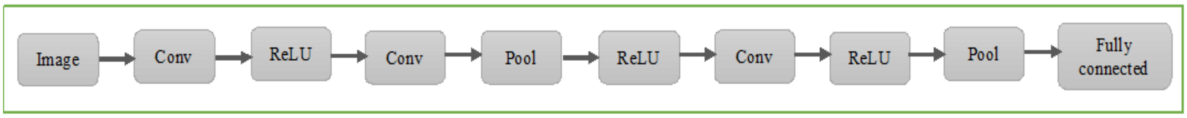

Figure 1: Structure of Convolutional Neural Network

The techniques used in the CNN include max pooling, Rectified Linear Unit (ReLU) and / or Softplus. Using ReLU, CNN absorb non-linear functions, allowing for better predictions. ReLU replaces negative pixel values such as blank spaces with zero. Next, max pooling is initialised in the reduction of feature map dimensionality, at the same time also maintains sensitive informations. This results in the reduction of network's computational complexity.

Max Pooling

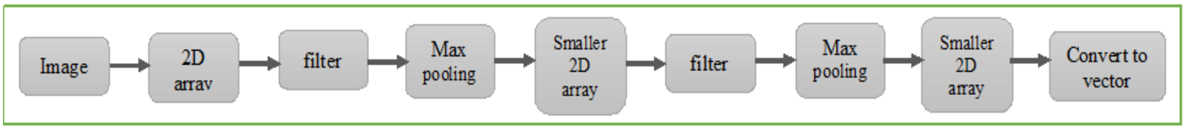

Figure 2:Process of Max Pooling

The machine learning model which uses Keras and TensorFlow along with labelled datasets usually achieve an optimal model using gradient descend. To adjust for overfitting or underfitting of the model, the researchers will monitor the progress of training and apply regularization techniques. The outcome can be improved by gathering more data or use transfer learning.

3. RESULTS AND DISCUSSIONS

3.1 Analysis of data collected through Observation

The analytical model will be tested on its accuracy using the validation dataset. The prediction model is a black box because there is no way of knowing how predictions are made. Using the output of the model, a confusion matrix was plotted, and performance of an analytical model is calculated.

Confusion Matrix and Accuracy

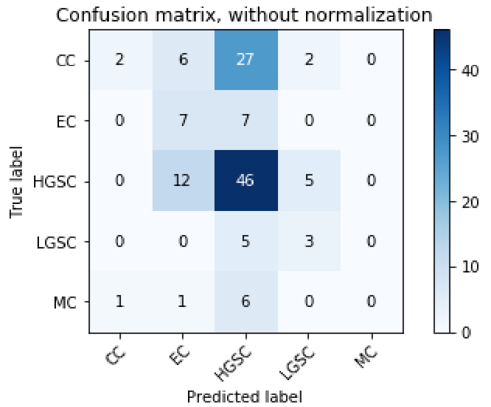

Figure 3: Confusion Matrix

Confusion matrix, shows the model performance based on true negatives, true positives, false negative and false positive (Markham, 2014).

The baseline of the dataset can be calculated by using the formula:

$$Baseline = \frac{Total\ number\ of\ images\ of\ the\ largest\ categorical\ class}{Total\ number\ of\ images} \quad (1)$$

The baseline results to 150/400 which is equivalent to 0.375.

Baseline and Accuracy

The baseline is the minimum accuracy target the machine learning model should have. If the machine learning model accuracy is more than 37.5%, it shows that the machine learning model is working to a certain degree. The machine learning model is accurate 89% of the time out of 130 images spanned over 5 categories.

Precision

Of all correct predictions, how many of them are true positive?

Precision answers that question. Precision denoted as a ratio of true positive predictions and total positive predictions. Therefore, high precision is in direct relation to low false positive rate. Precision calculation for an implemented machine learning models is **0.8482783883**. The calculation shows that the model is **precise**.

Recall

Recall is otherwise known as Sensitivity. Its a ratio of true positive to entire predictions. The average recall calculated is **0.8318425568**. It is below 0.5 and therefore, can be considered good.

F1 Score

"*Weighted average of Precision and Recall is referred as F1 Score*" - Renuka Joshi (Joshi, 2016)

F1 Score is useful when there is uneven class distribution of images. Comparitively F1 score performs better than accuracy in predicting the performance of machine learning model. In this case, the F1 Score is 0.835 which is above the usable rate of 0.5.

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Training

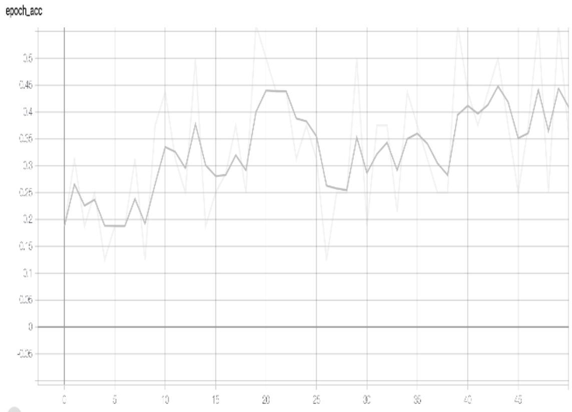

Figure 4: Accuracy vs number of epoch training

Figure 4 shows the improvements made by the machine learning model when trained. There is a general trend towards **higher accuracy.** However, the model was not able to reach the highest accuracy possible due to the lack of datasets.

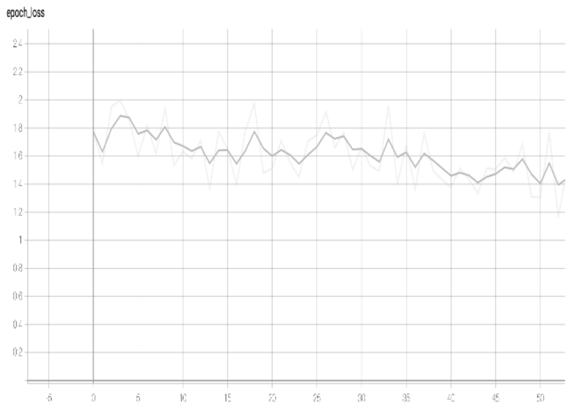

Figure 5: Loss vs number of epoch training

Figure 5 shows the downward trend of loss vs the number of times it has trained. Loss in this context represents the amount of errors made for each example in training. Therefore, the lower the loss, the better the accuracy of the model.

3.2 Analysis of data collected through Documents and Records

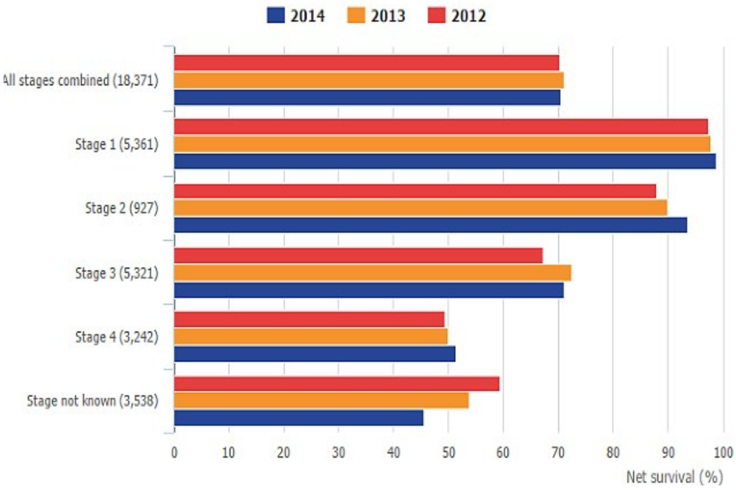

Figure 6: Bar chart of stages of ovarian cancer detection against survival rate (Pickles, 2016)

Early Diagnosis and awareness are key

The bar chart in Figure 12 evidently show an upward trajectory for every passing year, the ovarian cancer survival rating for stage 1 and 2 is high and has increased. This shows the survival rate and an importance of early diagnosis of ovarian cancer. Statistics and studies have shown the lacking diagnosis percentage of initial stage ovarian cancer, currently at 20% to 30% (American Cancer Society (c), n.d.; Fishman, 2018; Pickles, 2016). The standpoint is backed up by Fox et al., with a paper published in 2015 stating that genetic tests following diagnosis is preferential as the BRCA1 or BRCA2 gene mutation could cause more complications. The advanced knowledge of these genetic mutation provides the patient with a heads up to look out for breast cancer (Fox et al., 2015).

Restoring Fertility for preliminary stage of ovarian cancer patients

Zanetta et al conducted a research with a group of ovarian cancer patients who wished to bear children in the future. They found that the conservative treatment had more successful with patients in the early stage of ovarian cancer. Similar reports were found in the paper by Zapardiel, Diestro. and Aletti in 2014, with some success in restoring fertility in

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early onsets of ovarian cancer. To restore fertility to these patients, they have to be diagnosed early. Therefore, their findings support the project requirement in developing an ovarian screening system using AI.

Rising cost of diagnosis

The cost of biopsies in Malaysia is in the range of RM 2,800+ depending on the service provider (Shamasundari, 2016). Meanwhile, the cost of ultrasound scan of the pelvis costs RM 90 (Fertility Associates Malaysia, 2016). If the ML model prove to be accurate in detecting ovarian cancer with the ultrasound, cost of diagnosis would drop.

3.3 Analysis of data collected through Data Gathering

The data collected can be divided into 5 classes, clear cell ovarian histopathology images, endometrioid, high-grade serous, low-grade serous and mucinous. The dataset included an Excel Sheet of information on these slides with an expert diagnosis. These images are **categorised by Martin Kobel** from University of Calgary, Pathology and Laboratory Medicine expert. To the untrained eye, the researcher could not distinguish the histopathology images. Therefore, as intended, the analysis of the datasets is irrelevant as the pattern recognition is left to the machine learning. The machine learning model should be able to infer the diagnosis based on the histopathology image given.

Examples of these histopathology images are attached below:

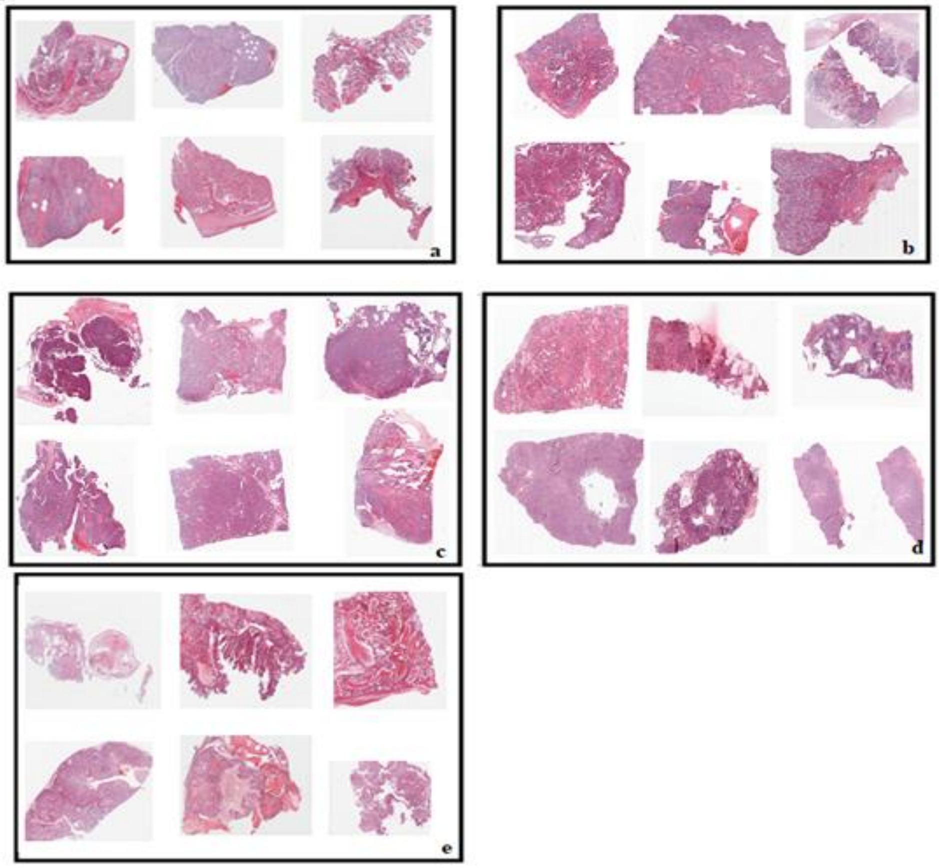

Figure 7: a)Clear Cell (CC), b) Endometrioid carcinoma (EC), c) High-grade serous carcinoma (HGSC), d) Low-grade serous carcinoma (LGSC), e) Mucinous carcinoma (MC)

Figure 7(a), shows the histopathology images of clear cell. Clear cell represents the ovaries are healthy. The histopathology images in Figure 7(b) are diagnosed with endometrioid. EC is an aggressive form of cancer that causes the growth of tumours (Levitan, 2017). HGSC is a type of tumour that arises from the serous epithelial layer mainly found in the ovary (Pölcher et al., 2015). The World Health Organization classification system of ovarian cancer differentiates HGSC and LGSC as two distinct diseases because the cause of LGSC is known to develop through serous borderline precursor lesions while HGSC does not (Grisham, 2016Mucinous carcinoma is a type of cancer relating to or covered with mucus cells (National Cancer Institute, 2019).

3.4 System Implementation

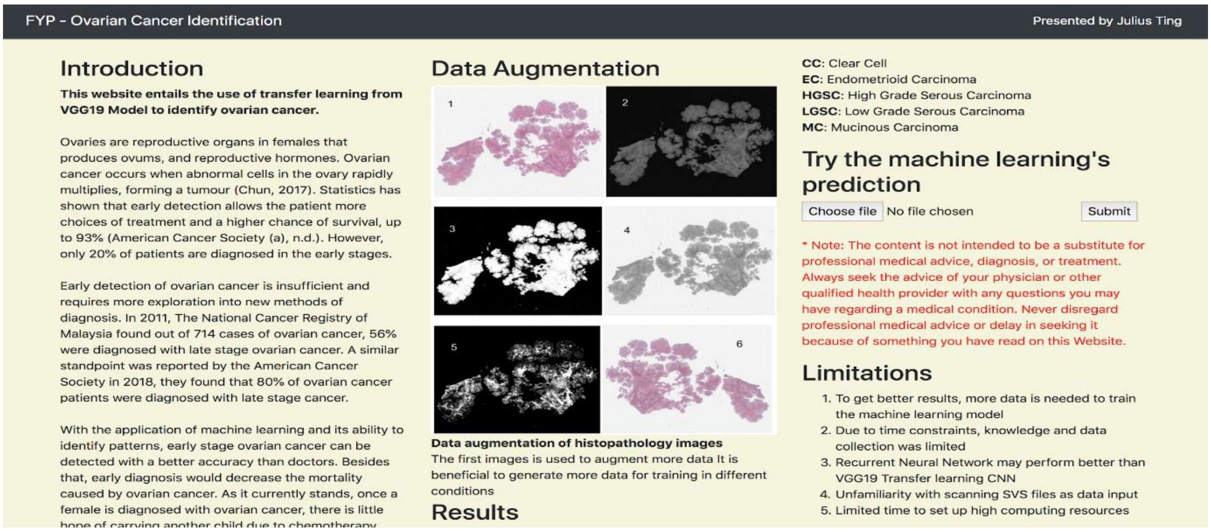

Figure 8: Website Homepage

As the machine learning model is the main objective of the project, the website was built minimally. The website can be found at: https://ovarian-cancer-detection.appspot.com

Figure 9: Prediction Page

The prediction page shows the uploaded image and the prediction of the machine learning model.

4. CONCLUSION

Artificial Intelligence is here to stay. AI is beneficial to us in many ways and we use it in my daily lives such as the usage of speech recognition to transcribe

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into text or from one language to another language using translation ML. This investigation report discusses the role of machine learning in healthcare and the accuracy of some developed ML models.

Tech giants such as Google and IBM are investing resources into the development of health screening using machine learning. By providing health screening services using machine learning, it would drastically reduce the cost of diagnosis, free up resources for pathologist to work on other cases and more importantly, bring access to healthcare to the masses. Ovarian cancer consider as a serious condition with high mortality when diagnosed during later stages. Machine learning has the potential of solving the issue of missed diagnosis and misdiagnosis for ovarian cancer. The researcher would be using Python and its open source packages to develop a CNN model, capable of identifying ovarian cancer.

Although the machine learning model could only attain an accuracy of 45%, it shows that machine learning could potentially be implemented in a vase number of industries. As progress is being made in machine learning techniques, someone may discover a better way of constructing a machine learning model.

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