Optimizing Skin Cancer Classifiers By Applying Multiplicative Weight Update Into A Mobile Application

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Abstract:

This study deals with using Artificial Intelligence and Machine Learning in order to create models that can diagnose skin cancer using images. Many models have been created in the past using different algorithms and methods. In this study, the multiplicative weight update method is used in order to take the predictions of multiple models in order to try and acquire more accurate predictions. In this study, a Logistic Regression, CNN, and SVC model are used. These models are sent images of skin cancer from the ISIC-Archive and they try to recognize patterns in order to categorize new images. These models are all then sent to a multiplicative weight update algorithm which takes into account the precision and accuracy of each model through each successive guess in order to add weight to their guess. These guesses are then added together in order to try and find the correct predictions. Using Multiplicative Weight Update, the model received an accuracy of 74.69%. The conclusion was made that using an SVC model would be the best option for this problem rather than a Multiplicative Weight Update system.

Introduction / Background:

Skin cancer is slowly becoming the most common and frequent type of cancer in the world. In the United States alone, research suggests that skin cancer is the most common cancer in and that one in every five people will acquire skin cancer at some point throughout their lifetime [2]. Globally, skin cancer affects over 108,000 people [1]. There are two primary categories often used to categorize types of skin cancer: melanoma and non-melanoma. Within the United States, there have been approximately 1,200,000 people diagnosed with non-melanoma cancer. This type of cancer refers to a group of cancers that slowly develop in the upper layers of the skin and start in the basal cells [3]. Melanoma, a much more severe type of cancer, develops in the melanocytes. These are cells that produce melanin — the pigment that gives your skin its color. Melanoma metasizes when these melanocytes start to grow uncontrollably [4]. Over 99,000 people are affected by melanoma of the skin [1]. Some other various types of skin cancer include:

- Actinic keratosis
- Recurrent basal cell carcinoma
- Squamous cell carcinoma
- Basal cell carcinoma
- Merkel cell carcinoma
- Melanoma
- Kaposi sarcoma (KS)
- Lymphoma of the skin
- Keratoacanthoma [5]

Melanoma is one least invasive yet one of the most dangerous and fatal types of cancer. Between 2009-2019 the number of new invasive melanoma cases diagnosed in the U.S. is estimated to have increased by over 40% [7]. In addition, within the United States, the percentage of people who develop melanoma has more than doubled in the past 30 years. It is estimated that in 2022, there will be 197,700 cases of melanoma diagnosed and of those, there will be 7,650 deaths from the disease [1].

If a melanoma diagnosis comes at an early stage, before the cancer has spread too much or caused too much damage, then this can significantly reduce the mortality rate due to this cancer [8]. In the last decade, with the advancement of image classification and artificial intelligence, various algorithms and models have been developed to solve this problem. Image processing and classification in the medical industry have been proven to be effective as identifying patterns like cancer from images reduces human errors and increases the speed of detection. In addition, these algorithms and models have the ability to help physicians and radiologists in the field who may require a second opinion in order to easily diagnose the disease.

Each algorithm has its own mathematical functions and commands that allow it to make the most accurate predictions it possibly can. However, no algorithm is 100% perfect. Certain algorithms may prove to be accurate in certain situations more than other algorithms. Here, a multiplicative weights update method could be applied.

Dataset:

The data consists of two folders each with 1800 pictures of melanoma and nonmelanoma moles. Each picture is 224 x 224 pixels and the dataset used was from the ISIC-Archive. The dataset was already split into train and test with 1440 benign training images, 1197 malignant training images, 360 benign testing images, and 300 malignant testing images. Each image was converted into an RGB array (3 x 224 x 224) for training and testing purposes.

Methodology/Models:

Multiplicative Weight Update

The output of this algorithm is dependent on the output of multiple different algorithms and applying multiplicative weight update to these outputs. The multiplicative weights update method is an algorithmic process, often used in game theory and algorithm design, used to optimize decision making, precision, and accuracy. The method is used to optimize for better predictions among a group of experts, or in this case, algorithms. The main purpose here is to optimize for the best algorithms depending on how they are performing throughout testing phases. In this way, higher accuracy may be able to be reached as multiple classifiers are collectively coming to a decision depending on how accurate they are individual as opposed to just one model.

In the setup of a multiplicative weight update system, a general binary decision must be made by each of the classifiers. In this study, the technique is employed for the diagnosis of cancer images. At first, each of the classifiers has an equal weight. In this study, with 3 different algorithms, each algorithm attained a starting weight of 0.33. The algorithm will make the first decision based on the majority of the algorithm decisions. Next, after each round is completed, the algorithm will update the weights of each of the algorithms depending on the accuracy of the algorithms in their prior predictions. For correct predictions, the weights remain the same, but for incorrect predictions, the weights are halved. Next, since the sum of the weights have been changed, the weights are adjusted to fit within the sum of the weights by dividing each weight by the sum of the weights; this ensures that the sum of the weights still add up to 1.

SVC

The Support Vector Classifiers (SVC) are supervised learning algorithms that utilize labeled data of different categories in order to categorize new data. In this study, they are provided the training images with labels of benign/malignant. The SVC draws a decision boundary between the categories of malignant and benign using the data is has been given. With this decision boundary, it is able to categorize new data by plotting it and understanding which side of the decision boundary the data lies on. The SVC model from sklearn.svm was used in this study.

Convolutional Neural Network

CNNs or convolutional neural networks take input images, process them, and are able to classify them under different categories. CNNs consist of an input layer, hidden layers, and an output layer. The input layer in this study accepts the image and the output layer classifies the image as benign or malignant. The hidden layers in the middle help to classify the image. Throughout each layer, "neurons" work to find connections between pixels throughout the images in order to understand patterns. Each neuron leads to the next layer and also holds its own weight which helps it in further layers. For example, in a 6-layer CNN, if the first layer would take the image in, the second layer may work to find lines in the image, and the third layer may function to find corners or curves in the image by using the lines found in the previous layer, the fourth layer would then try and put these corners, curves, and lines together in order to make shapes, finally, the fifth layer would put multiple shapes, corners, and lines together in order to fully classify the image and output a result in the sixth and final layer.

Logistic Regression

Logistic Regression belongs to the family of supervised machine learning models. The Logistic Regression model uses a logistic function that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits. These limits help to set the boundaries for classifying the data as malignant or benign. The model works by inputting values that correlate to pixel values along with weights for each value into this logistic function. If the function outputs a value below or above a certain threshold, it will be classified accordingly. For example, if the threshold for malignancy is 0.5, then any value that comes out of the function above 0.5 will be classified as malignant.

Results and Discussion

Each model performed well individually, some doing better than others. See the figure below for each model's accuracy.

Model	Training Accuracy	Testing Accuracy
SVC	80.05	78.48
CNN	60.78	63.03
Logistic Regression	79.97%	73.78

This figure shows that the SVC and Logistic Regression had the greatest starting accuracies going into Multiplicative Weight Update.

Overfitting was not a problem in this study because the training and testing accuracies were very close to each other. If we had the problem of overfitting, we could solve this with dropout or regularization techniques.

Using Multiplicative Weight Update, the model received an accuracy of 74.69%. We can also see that the Logistic Regression model took the most precedence as the models continued running through multiple rounds. Both the SVC and CNN had weights near 0 while the Logistic Regression model maintained a weight well over 0.9.

Overall, through this, we've found that Multiplicative Weight Update does not help much because certain algorithms perform much better than others and overtake them within a couple of rounds. This leads to dominating predictions within the algorithms.

These algorithms may also have performed poorly because they were limited to 500 images within the dataset. The machine running the algorithms did not have the computing power to handle more than 500 images without crashing. In addition, we were unable to rotate the images in order to add images of different orientations into the dataset. This might have increased the scope of the model and possibly increased its accuracy.

Conclusion

Overall, this research study has shown that combining models together using Multiplicative Weight Update is not always successful because Multiplicative Weight Update prioritizes the strong models much more than the other ones leaving them obsolete and their opinions unused. For this case, just using the SVC model would be the best option as it yielded the highest accuracies among all the models. As a result of this project, many questions have been raised and possible ventures have come up. For this study, the dataset had to be limited to

500 images because of the processing capacity of the machine running it. If this algorithm had been run on a better computer, the model possibly could have performed better or returned a different outcome. In addition, in future studies, it may be viable to pre-process the data differently by rotating each image to get it in different orientations. This would also require a higher capacity computer in order to run these programs and process all this data. To add on, more models could be added to this algorithm in order to see if adding more algorithms possibly increases the accuracy of the Multiplicative Weight Update system.

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References:

[1]

American Cancer Society. Cancer Facts & Figures 2022. Atlanta: American Cancer Society; 2022, https://www.cancer.org/content/dam/cancer-org/research/cancer-facts-and-statistics/annual-cancer-facts-and-figures/2022/2022-cancer-facts-and-figures.pdf

[2]

S. Stechschulte, C. Ricotti, C. J. Cockerell, Advances in diagnostic testing for skin cancer, TOUCH BRIEFINGS (2008) 73–76.

[3]

NHS. "Skin Cancer." *NHS Choices*, NHS, https://www.nhs.uk/conditions/non-melanoma-skin-cancer/#:~:text=Non%2Dmelanoma%20skin%20cancer%20refers,which%20can%20be%20more%20serious.

[4]

Mayo Clinic Staff. "Melanoma." *Mayo Clinic*, Mayo Foundation for Medical Education and Research, 18 June 2022, https://www.mayoclinic.org/diseases-conditions/melanoma/symptoms-causes/syc-20374884.

[5]

Skin Cancer Classification Using Deep Learning. http://dspace.uiu.ac.bd/bitstream/handle/52243/2483/Skin%20Cancer%20Classification%20-%202%20July%202022.pdf?sequence=1.

[6]

"Tests to Diagnose Skin Cancer." *Tests to Diagnose | Skin Cancer | Cancer Research UK*, 20 Sept. 2019, https://www.cancerresearchuk.org/about-cancer/skin-cancer/getting-diagnosed/tests-diagnose.

[7]

American Cancer Society. "Cancer Facts and Figures 2020". Atlanta: American Cancer Society; 2020.

[8]

Cohen, Victoria. Staging Uveal Melanoma with Whole-Body Positron-Emission Tomography/Computed Tomography and Abdominal Ultrasound: Low Incidence of Metastatic Disease, High Incidence of Second Primary Cancers. Meajo, http://www.meajo.org/article.asp?issn=0974-9233;year=2018;volume=25;issue=1;spage=25;epage=29;aulast=Baarah.