Paper Title\* (use style: *paper title*)

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*Abstract*—This paper will use four machine learning mythologies for classifying the Diabetic Retinopathy Severity Scale (DRSS) using the OCT images from OLIVES [1] dataset. This projects uses KNN, SVM, Alexnet, and Resnet18. Performances and potential improvements will be discussed in the following stections.

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# Introduction

Ophthalmology, a branch of eye treatment in medical field, is acquiring new technology of machine learning to predict patient prescriptions and treatments. In this study, the OLIVES dataset will be used, which contains detailed labeling of DRSS level of data images, to customize a machine learning model and measure predict the disease severity. The goal is to 7 levels of DRSS scores into 3 DRSS Severity Levels, and outputs of four different models will be used for accuracy comparison.

As no authors of this paper are particularly adept at interpreting OCT scans, in particular evaluating the severity of Diabetic Retinopathy [1], heuristics that could be used in conventional classification in image datasets such as ImageNet do not apply. The questions then arise of 1.How to correctly classify images from a dataset in which the designer of the training model knows very little about, and 2.Due to the size of the OLIVES dataset and its complexity, how to simplify and shorten the training time beyond image processing techniques, as any processing performed on the OCT frames may cause undesired information to be filtered. (include a figure of a OCT scan)

To tackle both issues mentioned, this paper makes an attempt to implement a new training method for CNNs mentioned in section III that references the psychological phenomenon of flashbulb memory.

# Different Methods Used

A total of four methods are used to attempt to classify the OCT frames, although more faith is placed into training AlexNet from scratch and training ResNet50 with transfer learning due to their superior computational complexity and CNN’s natural compatibility with images. Therefore, less innovation will be tried with the Naïve Bayes and Support Vectors Machines and only an autoencoder will be used to decrease computational time with those models.

## Naïve Bayes

The Naïve Bayes classification algorithm uses Bayes’ theorem’s conditional probabilities to classify new data.

## Support Vector Machines (SVM)

## Training New Weights on Alexnet

## Transfer Learning on ResNet50

# Training Methods

## Autoencoder

Due to the size of each frame being 504 x 496 pixels, the input to the Naïve Bayes and SVM models would be millions of dimensions as indicated in equations 1 and 2. This would be far too computationally expensive, both in resources and time to achieve over the length of the entire OLIVES dataset. Therefore, an autoencoder is used to decrease the representation of a frame down to the ten most significant dimensions.

## Pre-Processing

Although the size of the frames is not an issue with the Naïve Bayes or SVM algorithms because as mentioned previously they are mostly to test the complexity of the dataset. AlexNet and ResNet50 were trained and designed with a specific image size in mind and the OCT frames shall be resized to respect this architecture. They will also be normalized with the mean and standard deviation of the grey scale values of the entire dataset.

In addition, through inspection of the OLIVES dataset, the training and testing set data are interpreted to be structured as such: 49 OCT scan frames are generated per visit that the patient makes. Each patient makes a visit every 4 or 8 weeks for a total of 104 weeks, or 2 years. Assuming that the DRSS value of the patient’s eye does not change in the duration of a single visit, it’s reasonable that at least the 49 frames generated in that particular visit can be “bundled” together to train at once, as they are with the same patient in the same visit. This bundling is done via 3D convolution and should speed up the training process. But this is in comparison to training the models frame by frame and may be sacrificing some accuracy. Therefore with the flashbulb training detailed below which is already an attempt at a time saving technique, the two CNN models will be trained frame by frame with their labels rather than through a combination of multiple frames.

## Flashbulb Training

For both Alexnet and ResNet50 architectures, the model is trained using primarily a single class, then late into the training process a combined 3D-convoluted image made of multiple instances (volumes) of an alternative class is introduced with a higher learning rate, and trains the model for few or one epochs. The method of training is inspired by the psychological phenomenon of “flashbulb memory”(cite) where in which it is observed that the human brain experiencing a dramatic/emotionally significant event tends to remember it in high detail and that the event lasts for a extended period amount of time in the brain compared to everyday occurrences. Thus the term “flashbulb training” is coined for this training method.

Similarly, from the view of an optometrist who is used to only seeing a certain severity label, say of example level 2, then they may recognize a level 0 instance if they had only met it a select few times before, as it would be considered a rare example. In this example, the “everyday occurrence” would be the patients whose OCT scans indicated a DRSS severity level of 2 and the significant event to generate the “flashbulb memory” would be the patient whose OCT scan in a certain eye indicated a DRSS severity of level 2. This can also be generalized into other fields, not just optometry and in extension, image processing. Of course, the assumption is made here that the class introduced late into the training process is rare, which may not be the case.

As a neural network mimics the brain via the neuron, connections and activation, this flashbulb memory training method should in theory “shock” the model with the high learning rate integrated in backpropagation of the introduced new class, leaving its “impression” in the weights of the model. An advantage of this training method is that the training time is decreased significantly, as only select examples of an alternative class is needed to train the network rather than using all training datasets in every epoch.

D.

# Results

## Naïve Bayes and SVM

## AlexNet Flashbulb Training

## ResNet50 Flashbulb Training

# Discussion

In addition to conventional classification methods using Naïve Bayes, SVMs, and two CNN architectures, Alexnet with re-trained weights and ResNet50 with transfer learning, a new method of flashbulb memory is attempted where a CNN model is initially trained on a single class to become “proficient” at predicting the specific label, then a

Currently, it is expected that the flashbulb memory training method should only work on neural networks that only have an output of few classes.

What’s interesting

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1. M. Prabhushankar, K. Kokilepersaud\*, Y. Logan\*, S. Trejo Corona\*, G. AlRegib, C. Wykoff, "OLIVES Dataset: Ophthalmic Labels for Investigating Visual Eye Semantics," in *Advances in Neural Information Processing Systems (NeurIPS 2022) Track on Datasets and Benchmarks*, New Orleans, LA,, Nov. 29 - Dec. 1 2022
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1. M. Prabhushankar, K. Kokilepersaud\*, Y. Logan\*, S. Trejo Corona\*, G. AlRegib, C. Wykoff, "OLIVES Dataset: Ophthalmic Labels for Investigating Visual Eye Semantics," in *Advances in Neural Information Processing Systems (NeurIPS 2022) Track on Datasets and Benchmarks*, New Orleans, LA,, Nov. 29 - Dec. 1 2022

Brown, R., & Kulik, J. (1977). Flashbulb memories. *Cognition, 5*(1), 73–99. [https://doi.org/10.1016/0010-0277(77)90018-X](https://psycnet.apa.org/doi/10.1016/0010-0277(77)90018-X)