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, we are going to use OLIVE dataset, which contains detailed labeling of DRSS level of data images, to customize a machine learning model and measure predict the disease severity. We classified 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 in the paper are adept at recognizing OCT images, in particular evaluating the severity of Diabetic Retinopathy [1], heuristics that could be used in conventional image classification do not apply. The question then arises of how to simplify the training process,

# Different Architectures Used

## Naïve Bayes

Naïve Bayes method is a way to predict the probability of a certain class with the feature given the probability of feature in a certain classes. Four parameters used are posterior probability, likelihood, class prior probability, and predictor prior probability, where posterior probability is the prediction of classes based on features provided. The equation that suppoprts this idea is listed below:

## Support Vector Machines (SVM)

The primary goal of SVM is to propagate dataset that not linearly separable to high dimension and identify a hyperplane to maximize the classification effect. To maximize the hyperplane distance with any data point, a technique called Maximal Margin Classifier is used to find the Maximal Margin hyperplane (MMH), which id ideally furthest from any training data. Training observations that lies on the margin boundary, or the support vector determines the MMH. Usually, the goal for SVM algorithm is to produce the parameters of the MMH.

## Training a New Alexnet

Alexnet is a revolutionary Convolutional Neural Network (CNN) architecture that was first designed in 2012. It consists of 8 layers, including 5 convolution layers, 2 fully connected layers, and 1 softmax layer. The pre-trained Alexnet is available in the pytorch package, but it will not be used in this approach. Training from scratch means that the original structure of Alexnet will be retained, but the model uses all the OCT image data to train the network from blank. This method is computation heavy, but the design will be specific to desired dataset.

## Transfer Learning on ResNet50

The idea of transfer learning is to start the training with a pre-trained model. ResNet50 is another Convolutional Neural Network (CNN) that is provided by torch library and pre-trained by engineers. We will begin with the pre-trained ResNet50 and fine-tune the last few layers to make it suitable for the DRSS prediction task.

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# Training Methods

## Autoencoder

Due to the size of each frame, the input to the Naïve Bayes and SVM architectures would be millions of dimensions as indicated in equation. This would be far too computationally expensive, both in resources and time to achieve over the length of the .

Therefore, an autoencoder is used to abstract, or encode input images. Starting from an image size of 1x224x224, the autoencoder aims to encode each image to 2 dimensions only. We will train the convolution based autoencoder, once it gets a stable loss and reasonable accuracy, we will use it to do image encoding. From the encoded and condensed images, classification methods like SVM and KNN will be performed.

## Image Pre-Processing

## Flashbulb Memory 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 a person tends to remember a significant/traumatic event far more vividly than they do everyday occurrences. 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 rare few times before, as it would be considered a rare example. This can also be generalized into other fields, not 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.

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# Results

## Naïve Bayes and SVM

As mentioned previously,

## Training ResNet50 Frame-by-Frame

Prior to gaining an understanding of the OLIVES dataset, the method of ResNet50 with transfer learning was trained frame by frame.

# 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.

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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)