# Final Report

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#### Introduction

Alzheimer's disease is

We decided to use an Alzheimer's MRI imaging dataset from Kaggle. The data includes a total of 6400 MRI images from individuals classified into four stages: no dementia, very mild dementia, mild dementia, and moderate dementia. Each MRI result is a 128x128 .jpg image. The images have been preprocessed so that they are of a standard form and orientation, but we still will need to do the step of processing the data and gray scale standardization from .jpg images into a tabular format suitable for standard R functions.

#### Data Read-In

We read in the 128x128 images from .jpg files to three dimensional arrays, with the first element coresponding to the index

```
no_dementia \leftarrow array(NA, dim = c(3200, 128, 128))
for (i in 1:3200){
  no_dementia[i,,] <- readJPEG(pasteO(getwd(),</pre>
                                         "/Data/Non_Demented/non_", i, ".jpg"))
verymild_dementia <- array(NA, dim = c(2240, 128, 128))</pre>
for (i in 1:2240){
  verymild_dementia[i,,] <- readJPEG(pasteO(getwd(),</pre>
                                                "/Data/Very_Mild_Demented/verymild_", i, ".jpg"))
}
mild_dementia \leftarrow array(NA, dim = c(896, 128, 128))
for (i in 1:896){
  mild_dementia[i,,] <- readJPEG(pasteO(getwd(),</pre>
                                           "/Data/Mild_Demented/mild_", i, ".jpg"))
}
moderate_dementia <- array(NA, dim = c(64, 128, 128))
for (i in 1:64){
  moderate_dementia[i,,] <- readJPEG(pasteO(getwd(),</pre>
                                               "/Data/Moderate_Demented/moderate_", i, ".jpg"))
}
lenNoDem <- 3200
lenVeryMildDem <- 2240</pre>
lenMildDem <- 896
lenModDem <- 64
totalLen <- lenNoDem + lenVeryMildDem + lenMildDem + lenModDem
```

### Model 1: 3 classes with one hot encoding

```
lenNoDem <- 3200
lenVeryMildDem <- 2240</pre>
lenMildDem <- 896
lenModDem <- 64
img rows <- 128
img_cols <- 128</pre>
totalLen <- lenNoDem+lenVeryMildDem+lenMildDem+lenModDem
noDemClass <- cbind(rep(1,lenNoDem), rep(0,lenNoDem),</pre>
                     rep(0,lenNoDem))
veryMildDemClass <- cbind(rep(0,lenVeryMildDem), rep(1,lenVeryMildDem),</pre>
                            rep(0,lenVeryMildDem))
mildModDemClass <- cbind(rep(0,lenMildDem+lenModDem), rep(0,lenMildDem+lenModDem),
                          rep(1,lenMildDem+lenModDem))
classMat <- rbind(noDemClass,</pre>
                   veryMildDemClass,
                   mildModDemClass)
noDemTestIdx <- sample(lenNoDem, round(lenNoDem/4.0), replace = FALSE)</pre>
noDemTrainIdx <- setdiff(1:lenNoDem, noDemTestIdx)</pre>
veryMildDemTestIdx <- sample((lenNoDem+1):(lenNoDem+lenVeryMildDem),</pre>
                                round(lenVeryMildDem/4.0), replace = FALSE)
veryMildDemTrainIdx <- setdiff((lenNoDem+1):(lenNoDem+lenVeryMildDem),</pre>
                                veryMildDemTestIdx)
mildModDemTestIdx <- sample((lenNoDem+lenVeryMildDem+1):</pre>
                            (lenNoDem+lenVeryMildDem+lenMildDem+lenModDem),
                            round((lenMildDem+lenModDem)/4.0), replace = FALSE)
mildModDemTrainIdx <- setdiff((lenNoDem+lenVeryMildDem+1):</pre>
                            (lenNoDem+lenVeryMildDem+lenMildDem+lenModDem),
                            mildModDemTestIdx)
x_train <- dementia_data[c(noDemTrainIdx,veryMildDemTrainIdx,</pre>
                             mildModDemTrainIdx),,]
y_train <- classMat[c(noDemTrainIdx,veryMildDemTrainIdx,</pre>
```

```
mildModDemTrainIdx),]
x_test <- dementia_data[c(noDemTestIdx,veryMildDemTestIdx,</pre>
                           mildModDemTestIdx),,]
y_test <- classMat[c(noDemTestIdx,veryMildDemTestIdx,</pre>
                      mildModDemTestIdx),]
shuffleIdx <- sample(1:round(3.0*totalLen/4.0))</pre>
x train <- x train[shuffleIdx,,]</pre>
y_train <- y_train[shuffleIdx,]</pre>
x_train <- array_reshape(x_train, c(nrow(x_train), img_rows, img_cols, 1))</pre>
x_test <- array_reshape(x_test, c(nrow(x_test), img_rows, img_cols, 1))</pre>
input_shape <- c(img_rows, img_cols, 1)</pre>
batch_size <- 32</pre>
num_classes <- 3</pre>
epochs <- 100
mod1 <- keras_model_sequential() %>%
  layer_conv_2d(filters = 64, kernel_size = c(3,3),
                 activation = 'relu', input_shape = input_shape) %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_dropout(rate = 0.25) %>%
  layer_conv_2d(filters = 64, kernel_size = c(3,3),
                activation = 'relu', input_shape = input_shape) %>%
  layer_max_pooling_2d(pool_size = c(2, 2)) %>%
  layer_dropout(rate = 0.25) %>%
  layer flatten() %>%
  layer dense(units = 128, activation = 'relu',
              kernel_regularizer=regularizer_l1_l2(l1=1e-4,l2=1e-5)) %>%
  layer_dropout(rate = 0.25) %>%
  layer_dense(units = num_classes,
              activation = 'softmax')
mod1 %>% compile(
  loss = loss_categorical_crossentropy,
  optimizer = optimizer_adam(),
 metrics = c('accuracy')
cnn_history <- mod1 %>% fit(
  x_train, y_train,
  batch_size = batch_size,
  epochs = epochs,
  validation_split = 0.2
# Predict on the test data
predictProbs = predict(mod1, x_test)
saveRDS(predictProbs, file = "predict_mod1.Rds")
```

## Process Model 1 Results

```
predictProbs = readRDS("predict_mod1.Rds")
predictClass <- matrix(NA, nrow = nrow(x_test), ncol = num_classes)</pre>
for (i in 1:nrow(x_test)) {
  classVec <- rep(0, num_classes)</pre>
  classVec[which(predictProbs[i,] == max(predictProbs[i,]))] <- 1</pre>
  predictClass[i,] <- classVec</pre>
testAccuracyNoDem <- 0.0</pre>
testAccuracyVeryMildDem <- 0.0
testAccuracyMildModDem <- 0.0</pre>
diffMat <- y_test - predictClass</pre>
for (i in 1:length(noDemTestIdx)) {
  testAccuracyNoDem <- testAccuracyNoDem+ifelse(min(diffMat[i,]) == 0,1,0)</pre>
for (i in 1:length(veryMildDemTestIdx)) {
  testAccuracyVeryMildDem <- testAccuracyVeryMildDem +</pre>
    ifelse(min(diffMat[length(noDemTestIdx)+i,]) == 0,1,0)
for (i in 1:length(mildModDemTestIdx)) {
  testAccuracyMildModDem <- testAccuracyMildModDem +</pre>
    ifelse(min(diffMat[length(noDemTestIdx)+length(veryMildDemTestIdx)+i,]) == 0,1,0)
testAccuracyNoDem <- testAccuracyNoDem/length(noDemTestIdx)</pre>
testAccuracyVeryMildDem <- testAccuracyVeryMildDem/length(veryMildDemTestIdx)</pre>
testAccuracyMildModDem <- testAccuracyMildModDem/length(mildModDemTestIdx)</pre>
resModel1 <- data.frame("No Dementia" = testAccuracyNoDem,</pre>
                          "Very Mild Dementia" = testAccuracyVeryMildDem,
                          "Mild/Moderate Dementia" = testAccuracyMildModDem)
knitr::kable(resModel1)
```

No.Dementia	Very.Mild.Dementia	Mild.Moderate.Dementia
0.975	0.9214286	0.9625

## Model 2: 4 classes with one hot encoding

```
lenNoDem <- 3200
lenVeryMildDem <- 2240
lenMildDem <- 896
lenModDem <- 64

img_rows <- 128
img_cols <- 128

totalLen <- lenNoDem+lenVeryMildDem+lenModDem</pre>
```

#### Process Model 2 Results

```
predictProbs = readRDS("predict_mod2.Rds")
predictClass <- matrix(NA, nrow = nrow(x_test), ncol = num_classes)</pre>
for (i in 1:nrow(x_test)) {
  classVec <- rep(0, num_classes)</pre>
  classVec[which(predictProbs[i,] == max(predictProbs[i,]))] <- 1</pre>
  predictClass[i,] <- classVec</pre>
testAccuracyNoDem <- 0.0
testAccuracyVeryMildDem <- 0.0</pre>
testAccuracyMildDem <- 0.0
testAccuracyModDem <- 0.0</pre>
diffMat <- y_test - predictClass</pre>
for (i in 1:length(noDemTestIdx)) {
  testAccuracyNoDem <- testAccuracyNoDem+ifelse(min(diffMat[i,]) == 0,1,0)</pre>
for (i in 1:length(veryMildDemTestIdx)) {
  testAccuracyVeryMildDem <- testAccuracyVeryMildDem +</pre>
    ifelse(min(diffMat[length(noDemTestIdx)+i,]) == 0,1,0)
for (i in 1:length(mildDemTestIdx)) {
  testAccuracyMildDem <- testAccuracyMildDem +</pre>
    ifelse(min(diffMat[length(noDemTestIdx) +
                          length(veryMildDemTestIdx)+i,]) == 0,1,0)
for (i in 1:length(modDemTestIdx)) {
  testAccuracyModDem <- testAccuracyModDem +</pre>
    ifelse(min(diffMat[length(noDemTestIdx)+length(veryMildDemTestIdx)+
                          length(mildDemTestIdx)+i,]) == 0,1,0)
}
```

No.Dementia	$Very. \\ Mild. \\ Dementia$	${\bf Mild. Dementia}$	Moderate.Dementia
0.97875	0.9785714	0.9508929	0.875