# ML

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```
library(tidyverse)
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
           1.1.4
## v dplyr
                        v readr
                                    2.1.5
## v forcats 1.0.0
                        v stringr
                                    1.5.1
## v ggplot2 3.5.1
                       v tibble
                                    3.2.1
## v lubridate 1.9.3
                     v tidyr
                                    1.3.1
## v purrr
              1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                    masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
library(tidytext)
library(tm)
## Loading required package: NLP
## Attaching package: 'NLP'
## The following object is masked from 'package:ggplot2':
##
##
       annotate
library(textstem)
## Loading required package: koRpus.lang.en
## Loading required package: koRpus
## Loading required package: sylly
## For information on available language packages for 'koRpus', run
##
##
     available.koRpus.lang()
## and see ?install.koRpus.lang()
##
##
## Attaching package: 'koRpus'
## The following object is masked from 'package:tm':
##
```

```
##
       readTagged
##
## The following object is masked from 'package:readr':
##
##
       tokenize
library(caret) # Stratified Sampling
## Loading required package: lattice
##
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
##
       lift
library(dplyr)
library(e1071) # SVM
library(caret) # KNN
library(class) # KNN
reddit_data <- read.csv('merged_data.csv', stringsAsFactors = FALSE)</pre>
# Create stance based on score values
reddit_data <- reddit_data %>%
  mutate(stance = case when(
    score > 0 ~ "Favorable".
    score < 0 ~ "Oppose",</pre>
    TRUE ~ "Neutral"
  )) %>%
 mutate(stance = as.factor(stance))
```

After performing simple random sampling (SRS), only 400 records were retained. Such a random sample may lead to some issues. The original dataset includes three stance categories: Favorable, Neutral, and Oppose. However, after random sampling, the Neutral and Oppose classes may have extremely few samples, or even just 0 or 1 instance.

As a result, when performing cross-validation, training, or evaluating models such as K-Nearest Neighbors (KNN), the model is exposed almost exclusively to the Favorable class. This leads to evaluation metrics like Sensitivity or Positive Predictive Value showing NaN values.

These metrics are calculated as TP / (TP + FN). If the denominator is zero—such as when the model never predicts or encounters examples from a class—the result is NaN.

Therefore, stratified sampling was ultimately chosen to ensure that samples were drawn proportionally from each stance category, preserving class balance in the dataset.

```
# Stratified sampling (take proportional, fixed sample size from each stance)
set.seed(100)
sample_index <- createDataPartition(reddit_data$stance, p = 400 / nrow(reddit_data), list = FALSE)
reddit_data <- reddit_data[sample_index, ]

reddit_data$post_id <- as.character(reddit_data$comment_id)
sum(is.na(reddit_data$comment))</pre>
```

```
## [1] 0
sum(reddit_data$comment == "")
## [1] 0
glimpse(reddit_data)
## Rows: 401
## Columns: 12
## $ url
              <chr> "https://www.reddit.com/r/vaxxhappened/comments/1j55mqg/ant~
## $ author
             <chr> "SuggestiveParsnip", "Rugkrabber", "PrimeMinisterOwl", "IAm~
## $ date <chr> "2025-03-07", "2025-03-14", "2025-02-22", "2025-02-19", "20~
## $ timestamp <chr> "2025-03-06 19:15:39", "2025-03-14 08:46:57", "2025-02-22 1~
## $ score <int> 5, 1, 42, 11, 7, 25, 3, 11, 4, 7, 2, 70, 21, 107, 11, 15, 6~
## $ upvotes <int> 5, 1, 42, 11, 7, 25, 3, 11, 4, 7, 2, 70, 21, 107, 11, 15, 6~
## $ golds
            ## $ comment <chr> "bingo it\031s always about the money", "oh bullshit he mad~
## $ comment_id <chr> "3_2_1", "3_4_2_1_2_1", "7", "1_4", "2_1_1", "5", "35", "3_~
             <fct> Favorable, Favorable, Favorable, Favorable, Favorable
## $ stance
## $ post_id
              <chr> "3_2_1", "3_4_2_1_2_1", "7", "1_4", "2_1_1", "5", "35", "3_~
# Text preprocessing (using the comment column)
reddit_corpus <- Corpus(VectorSource(reddit_data$comment))</pre>
reddit_corpus <- tm_map(reddit_corpus, content_transformer(tolower))</pre>
## Warning in tm_map.SimpleCorpus(reddit_corpus, content_transformer(tolower)):
## transformation drops documents
reddit_corpus <- tm_map(reddit_corpus, removeNumbers)</pre>
## Warning in tm_map.SimpleCorpus(reddit_corpus, removeNumbers): transformation
## drops documents
reddit_corpus <- tm_map(reddit_corpus, removePunctuation)</pre>
## Warning in tm_map.SimpleCorpus(reddit_corpus, removePunctuation):
## transformation drops documents
reddit_corpus <- tm_map(reddit_corpus, removeWords, stopwords("english"))</pre>
## Warning in tm_map.SimpleCorpus(reddit_corpus, removeWords,
## stopwords("english")): transformation drops documents
reddit_corpus <- tm_map(reddit_corpus, lemmatize_words)</pre>
## Warning in tm_map.SimpleCorpus(reddit_corpus, lemmatize_words): transformation
## drops documents
```

```
# Build Term-Document Matrix
reddit_dtm <- DocumentTermMatrix(reddit_corpus)</pre>
# Remove sparse terms (appearing in less than 1% of posts)
reddit dtm <- removeSparseTerms(reddit dtm, 0.99)</pre>
# Convert to data frame
reddit_dtm_df <- as.data.frame(as.matrix(reddit_dtm))</pre>
reddit_dtm_df$post_id <- reddit_data$post_id</pre>
reddit_dtm_df$stance <- reddit_data$stance</pre>
glimpse(reddit_dtm_df)
## Rows: 401
## Columns: 320
## $ always
         ## $ money
         ## $ anyone
         ## $ back
         ## $ can
         <dbl> 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, ~
## $ choice
         ## $ fucking
         <dbl> 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, ~
## $ get
## $ just
         <dbl> 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ~
## $ made
         <dbl> 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ medical
         ## $ need
         ## $ now
         ## $ one
         ## $ people
         <dbl> 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, ~
## $ read
         ## $ right
## $ sick
         <dbl> 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0
## $ something
         ## $ told
         <dbl> 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0
## $ without
         ## $ dying
         ## $ going
         <dbl> 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, ~
## $ start
         <dbl> 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ thats
         <dbl> 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ well
         ## $ like
         ## $ said
         ## $ someone
         ## $ keep
         ## $ think
         <dbl> 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, ~
## $ afraid
         <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ even
         ## $ given
         <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ hell
         ## $ 'next'
         ## $ thevre
         <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, ~
```

```
## $ trump
          ## $ least
          <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
          <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ let
## $ please
          <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ take
          <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ already
          <dbl> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, ~
## $ iob
          <dbl> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
          <dbl> 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ post
## $ available
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, ~
## $ big
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ cases
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ death
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ doctors
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, ~
## $ far
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ kid
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, ~
## $ measles
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 1, 0, 0, ~
## $ theres
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ vaccine
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, ~
## $ yet
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ called
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ hate
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, ~
## $ important
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, ~
## $ means
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, ~
## $ old
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, ~
## $ vaccines
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, ~
## $ years
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, ~
## $ almost
          <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, ~
## $ 'don\031t'
          ## $ forget
          ## $ care
          ## $ chance
          ## $ didnt
          ## $ die
          ## $ died
          ## $ doesnt
          ## $ might
          ## $ prevent
          ## $ still
          ## $ children
          ## $ covid
          ## $ different
          ## $ effects
## $ enough
          ## $ flu
          ## $ happens
          ## $ immunity
## $ make
          ## $ never
          ## $ really
          ## $ reason
          ## $ saw
          ## $ school
          ## $ shot
          ## $ side
```

```
## $ test
  ## $ took
  ## $ absolutely
## $ imagine
  ## $ media
  ## $ dont
  ## $ everv
  ## $ fear
  ## $ vax
  ## $ conspiracy
  ## $ first
  ## $ know
  ## $ long
  ## $ months
  ## $ pretty
  ## $ things
  ## $ vaccinated
  ## $ heart
  ## $ new
  ## $ give
  ## $ immune
  ## $ system
  ## $ two
  ## $ virus
  ## $ better
  ## $ put
  ## $ poison
  ## $ data
  ## $ evidence
  ## $ infection
  ## $ symptoms
  ## $ want
  ## $ aliens
  ## $ saying
## $ anything
  ## $ away
  ## $ case
  ## $ either
  ## $ happened
  ## $ life
  ## $ literally
  ## $ much
## $ run
  ## $ sure
  ## $ theory
  ## $ though
## $ time
  ## $ wav
  ## $ '\031re'
  ## $ look
  ## $ see
  ## $ example
  ## $ healthcare
  ## $ human
```

```
## $ use
  ## $ also
  ## $ diseases
  ## $ except
  ## $ fine
  ## $ health
  ## $ illness
  ## $ likely
  ## $ risk
  ## $ understand
  ## $ worth
  ## $ infections
  ## $ strain
  ## $ cause
  ## $ decision
  ## $ good
  ## $ jab
  ## $ social
  ## $ thing
  ## $ thought
  ## $ country
  ## $ done
  ## $ 'didn\031t'
  ## $ got
  ## $ work
  ## $ world
  ## $ started
  ## $ masks
  ## $ live
  ## $ remember
  ## $ vaccination
  ## $ arent
  ## $ believe
  ## $ dead
  ## $ issue
  ## $ around
  ## $ getting
  ## $ ive
  ## $ large
  ## $ lot
  ## $ sometimes
  ## $ sounds
## $ whole
  ## $ wonder
  ## $ source
  ## $ previous
## $ sav
  ## $ killed
  ## $ pharma
  ## $ everyone
  ## $ last
  ## $ less
  ## $ ago
  ## $ instead
```

```
## $ makes
  ## $ making
  ## $ millions
  ## $ mrna
  ## $ study
  ## $ shots
  ## $ love
  ## $ rfk
  ## $ government
  ## $ trust
  ## $ cancer
  ## $ rates
  ## $ since
  ## $ using
  ## $ order
  ## $ guy
  ## $ late
  ## $ '\031ve'
  ## $ bad
  ## $ man
  ## $ many
  ## $ thanks
  ## $ mean
  ## $ spread
  ## $ will
  ## $ yes
  ## $ small
  ## $ sorry
  ## $ talking
  ## $ show
  ## $ specific
  ## $ actually
  ## $ year
## $ cant
  ## $ shit
  ## $ must
  ## $ healthy
  ## $ ill
  ## $ link
  ## $ point
  ## $ medicine
## $ bet
  ## $ find
  ## $ used
  ## $ isnt
  ## $ fact
  ## $ 'else'
  ## $ nothing
  ## $ says
  ## $ seems
  ## $ apply
  ## $ bot
  ## $ comment
```

```
## $ contact
  ## $ directed
  ## $ discussion
## $ general
  ## $ questions
  ## $ rest
  ## $ rule
  ## $ thread
  ## $ lab
  ## $ stupid
  ## $ wrong
  ## $ probably
  ## $ face
  ## $ 1mao
  ## $ matter
  ## $ ever
  ## $ guess
  ## $ kids
  ## $ story
## $ cold
  ## $ place
  ## $ feel
  ## $ little
  ## $ measures
  ## $ play
  ## $ talk
  ## $ term
  ## $ truth
  ## $ group
  ## $ known
  ## $ state
  ## $ true
  ## $ youre
  ## $ doctor
  ## $ high
  ## $ agree
  ## $ completely
  ## $ due
  ## $ end
  ## $ leak
  ## $ person
  ## $ lol
## $ public
  ## $ edit
  ## $ part
  ## $ news
## $ business
  ## $ day
  ## $ lets
  ## $ child
  ## $ problem
  ## $ come
  ## $ reading
  ## $ went
```

```
## $ daughter
      ## $ safe
      ## $ times
      ## $ obviously
      ## $ thinking
      ## $ possibly
      ## $ home
      ## $ positive
      ## $ within
      ## $ tested
      ## $ post_id
      <chr> "3_2_1", "3_4_2_1_2_1", "7", "1_4", "2_1_1", "5", "35", "~
## $ stance
      <fct> Favorable, Favorable, Favorable, Favorable, Favorable, Fa~
write.csv(reddit_data, "reddit_stratified_400.csv", row.names = FALSE)
```

## Dataset Split

```
# Data splitting (80% training, 20% testing)
set.seed(100)
test <- reddit_dtm_df %>% sample_frac(.2)
train <- reddit_dtm_df %>% anti_join(test, by = 'post_id') %>% select(-post_id)
test <- test %>% select(-post_id)

# Ensure valid feature names
colnames(train) <- make.names(colnames(train))
colnames(test) <- make.names(colnames(test))

test_raw <- reddit_dtm_df %>% sample_frac(.2)
write.csv(test_raw, "reddit_test_set_with_id.csv", row.names = FALSE)
```

#### Model Development

Support Vector Machine (SVM)

```
svm_model <- svm(stance ~ ., data = train, kernel = 'linear', cost = 1)

## Warning in svm.default(x, y, scale = scale, ..., na.action = na.action):
## Variable(s) 'means' and 'measures' and 'play' constant. Cannot scale data.

svm_pred <- predict(svm_model, test)
svm_cm <- confusionMatrix(svm_pred, test$stance)
print("SVM Confusion Matrix:")

## [1] "SVM Confusion Matrix:"</pre>
```

```
## Confusion Matrix and Statistics
##
##
             Reference
## Prediction Favorable Neutral Oppose
##
    Favorable
                  65
                              3
    Neutral
                      1
                              0
                                     0
##
     Oppose
##
##
## Overall Statistics
##
##
                 Accuracy : 0.8125
                   95% CI : (0.7097, 0.8911)
##
      No Information Rate: 0.875
##
##
      P-Value [Acc > NIR] : 0.9624
##
##
                     Kappa: -0.0118
##
##
  Mcnemar's Test P-Value: 0.4936
##
## Statistics by Class:
##
##
                       Class: Favorable Class: Neutral Class: Oppose
                                                0.0000
                                                              0.0000
## Sensitivity
                                 0.9286
## Specificity
                                 0.1000
                                                0.9868
                                                              0.9324
## Pos Pred Value
                                               0.0000
                                                              0.0000
                                0.8784
## Neg Pred Value
                                 0.1667
                                                0.9494
                                                              0.9200
## Prevalence
                                 0.8750
                                                0.0500
                                                              0.0750
## Detection Rate
                                 0.8125
                                                0.0000
                                                              0.0000
## Detection Prevalence
                                0.9250
                                                0.0125
                                                              0.0625
## Balanced Accuracy
                                 0.5143
                                                0.4934
                                                              0.4662
```

### K-Nearest Neighbors (KNN)

```
## predicted actual
## 1 Favorable Favorable
```

```
## 2 Favorable Favorable
## 3 Favorable Favorable
## 4 Favorable Favorable
## 5 Favorable Favorable
## 6 Favorable Favorable
# Confusion matrix and model performance metrics
knn_cm <- confusionMatrix(pred_actual$predicted, pred_actual$actual)</pre>
print("KNN Confusion Matrix:")
## [1] "KNN Confusion Matrix:"
print(knn_cm)
## Confusion Matrix and Statistics
##
              Reference
##
## Prediction Favorable Neutral Oppose
##
     Favorable
                      69
##
     Neutral
                       0
                                0
                                       0
##
     Oppose
##
## Overall Statistics
##
##
                  Accuracy : 0.8625
                    95% CI: (0.7673, 0.9293)
##
       No Information Rate: 0.875
##
       P-Value [Acc > NIR] : 0.7048
##
##
##
                     Kappa: -0.0185
##
   Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
                         Class: Favorable Class: Neutral Class: Oppose
##
## Sensitivity
                                   0.9857
                                                    0.00
                                                                 0.0000
                                   0.0000
                                                    1.00
                                                                 0.9865
## Specificity
## Pos Pred Value
                                   0.8734
                                                     {\tt NaN}
                                                                 0.0000
## Neg Pred Value
                                   0.0000
                                                    0.95
                                                                 0.9241
## Prevalence
                                                    0.05
                                   0.8750
                                                                 0.0750
## Detection Rate
                                                    0.00
                                                                 0.0000
                                   0.8625
## Detection Prevalence
                                   0.9875
                                                    0.00
                                                                 0.0125
## Balanced Accuracy
                                   0.4929
                                                     0.50
                                                                 0.4932
# Precision and Recall for each class (multi-class classification)
precision_recall <- knn_cm$byClass[, c("Pos Pred Value", "Sensitivity")]</pre>
print("Precision and Recall by Class (KNN):")
```

## [1] "Precision and Recall by Class (KNN):"

```
print(precision_recall)
##
                    Pos Pred Value Sensitivity
## Class: Favorable
                         0.8734177
                                      0.9857143
## Class: Neutral
                                      0.0000000
                                NaN
                          0.0000000
                                      0.0000000
## Class: Oppose
# Compute and display average Precision and Recall
avg_precision <- mean(precision_recall[, "Pos Pred Value"], na.rm=TRUE)</pre>
avg_recall <- mean(precision_recall[, "Sensitivity"], na.rm=TRUE)</pre>
cat("KNN Accuracy:", knn_cm$overall['Accuracy'], "\n")
## KNN Accuracy: 0.8625
cat("KNN Average Precision:", avg_precision, "\n")
## KNN Average Precision: 0.4367089
cat("KNN Average Recall:", avg_recall, "\n")
```

## KNN Average Recall: 0.3285714

To ensure that every stance category is represented in the dataset, stratified sampling was used instead of simple random sampling to select 400 data points.

However, the results of model development still show NaN or zero values. This is mainly due to the extremely imbalanced distribution of classes in the original data. Even with stratified sampling, categories like Neutral and Oppose may still have very few examples.

For instance:

If Neutral accounts for only 5% of the total data, it would contribute around 20 records to the sample. If Oppose accounts for 7.5%, that's only about 30 records.

After splitting the 400-sample dataset into 80% training and 20% testing, the test set might end up with only about 4 Neutral and 6 Oppose examples.

With such small numbers, the model may fail to detect these minority classes entirely—leading to sensitivity values of 0 and precision values of NaN.

#### Model Evaluation

```
# Function to calculate F1-score
calculate_f1 <- function(precision, recall){
    (2 * precision * recall) / (precision + recall)
}

# Calculate metrics for SVM
svm_accuracy <- svm_cm$overall['Accuracy']
svm_precision <- mean(svm_cm$byClass[, "Pos Pred Value"], na.rm=TRUE)
svm_recall <- mean(svm_cm$byClass[, "Sensitivity"], na.rm=TRUE)
svm_f1 <- calculate_f1(svm_precision, svm_recall)
cat("SVM metrics:", "\n","Accuracy:", svm_accuracy, "\n","Precision:", svm_precision, "\n","Recall:", svm</pre>
```

```
## SVM metrics:
## Accuracy: 0.8125
## Precision: 0.2927928
## Recall: 0.3095238
## F1 Score: 0.3009259
# Calculate metrics for KNN
knn_accuracy <- knn_cm$overall['Accuracy']</pre>
knn_precision <- mean(knn_cm$byClass[, "Pos Pred Value"], na.rm=TRUE)</pre>
knn_recall <- mean(knn_cm$byClass[, "Sensitivity"], na.rm=TRUE)</pre>
knn_f1 <- calculate_f1(knn_precision, knn_recall)</pre>
cat("KNN metrics:", "\n","Accuracy:", knn_accuracy, "\n","Precision:", knn_precision,"\n","Recall:", kn
## KNN metrics:
## Accuracy: 0.8625
## Precision: 0.4367089
## Recall: 0.3285714
## F1 Score: 0.375
# Compare based on Accuracy and F1 Score
if (svm_accuracy > knn_accuracy & svm_f1 > knn_f1){
  best_model <- svm_model</pre>
  best_model_name <- "SVM"</pre>
  best_cm <- svm_cm
  best_pred <- svm_pred</pre>
  best_accuracy <- svm_accuracy</pre>
  best_f1 <- svm_f1</pre>
} else {
  best_model <- "KNN"</pre>
  best_model_name <- "KNN"</pre>
  best_cm <- knn_cm
  best_pred <- knn_pred</pre>
  best_accuracy <- knn_accuracy</pre>
  best_f1 <- knn_f1</pre>
cat("Best Model Selected:", best_model_name, "\n")
## Best Model Selected: KNN
cat("Accuracy:", best_accuracy, "\n")
## Accuracy: 0.8625
cat("F1 Score:", best_f1, "\n")
## F1 Score: 0.375
# Compare predictions of the best model with manually assigned labels
result_df <- data.frame(</pre>
  Actual = test$stance,
```