PCR part

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We want to see if using principal components help with building the predictive model. ## Random Forest Model using Principal Components

```r
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.1
## v ggplot2   3.5.0     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 (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(ggplot2)
library(dplyr)
library(randomForest)
```

```
## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
library(tree)
library(lubridate)
library(grid)
library(glmnet)
```

```
## Loading required package: Matrix
```

```
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
##
## Loaded glmnet 4.1-8
```

```r
library(corrplot)
```

```
## corrplot 0.95 loaded
```

```r
library(tibble)
library(nnet)
set.seed(222)
final_previous_merged <- read.csv("final_previous_merged.csv") # load new dataset

final_previous_merged_updated<- final_previous_merged %>% mutate(risk= ifelse(FHR >= 80, "very low risk

# make sure all na values are converted to 0
final_previous_merged_updated[is.na(final_previous_merged_updated)] <- 0

# remove the curency conversion columns
valid_cols <- final_previous_merged_updated %>%
  select(where(is.numeric)) %>%
  select(-prev_X.Other.Currency.to.USD, -prev_inf_factor) %>%
  summarise(across(everything(), ~ mean(!is.na(.)))) %>%
  pivot_longer(everything(), names_to = "col", values_to = "non_na_ratio") %>%
  pull(col)

# also remove FHR to avoid it predicts itself
numeric_data <- final_previous_merged_updated %>%
  select(all_of(valid_cols)) %>%
  select(-FHR) %>%
  drop_na()

nrow(numeric_data)
```

```
## [1] 2591
```

```r
# use Principal Component for modeling, use prcomp function to find number of PCs being used
pca_result <- prcomp(numeric_data, scale. = TRUE)
summary(pca_result)
```

```
## Importance of components:
##                           PC1    PC2     PC3     PC4     PC5     PC6     PC7
## Standard deviation     5.6330 3.1808 1.38322 1.36807 1.27247 1.25719 1.09385
## Proportion of Variance 0.5471 0.1744 0.03299 0.03227 0.02792 0.02725 0.02063
## Cumulative Proportion  0.5471 0.7215 0.75451 0.78678 0.81469 0.84194 0.86257
##                            PC8     PC9    PC10    PC11   PC12    PC13    PC14
## Standard deviation     1.05610 1.02067 0.99751 0.89910 0.8913 0.74740 0.68511
```

```
## Proportion of Variance 0.01923 0.01796 0.01716 0.01394 0.0137 0.00963 0.00809
## Cumulative Proportion  0.88180 0.89977 0.91692 0.93086 0.9446 0.95419 0.96228
##                           PC15    PC16    PC17    PC18    PC19    PC20    PC21
## Standard deviation     0.65552 0.64473 0.56741 0.43240 0.41759 0.37859 0.34766
## Proportion of Variance 0.00741 0.00717 0.00555 0.00322 0.00301 0.00247 0.00208
## Cumulative Proportion  0.96969 0.97686 0.98241 0.98563 0.98864 0.99111 0.99319
##                           PC22    PC23    PC24    PC25    PC26    PC27    PC28
## Standard deviation     0.30195 0.25850 0.20352 0.19311 0.17775 0.15506 0.14966
## Proportion of Variance 0.00157 0.00115 0.00071 0.00064 0.00054 0.00041 0.00039
## Cumulative Proportion  0.99476 0.99592 0.99663 0.99727 0.99782 0.99823 0.99862
##                           PC29    PC30    PC31    PC32    PC33    PC34    PC35
## Standard deviation     0.12137 0.11653 0.09765 0.08924 0.08023 0.07513 0.06934
## Proportion of Variance 0.00025 0.00023 0.00016 0.00014 0.00011 0.00010 0.00008
## Cumulative Proportion  0.99887 0.99911 0.99927 0.99941 0.99952 0.99962 0.99970
##                           PC36    PC37    PC38    PC39    PC40    PC41    PC42
## Standard deviation     0.05421 0.05304 0.05013 0.04552 0.04282 0.04216 0.03526
## Proportion of Variance 0.00005 0.00005 0.00004 0.00004 0.00003 0.00003 0.00002
## Cumulative Proportion  0.99975 0.99980 0.99984 0.99988 0.99991 0.99994 0.99996
##                           PC43    PC44    PC45   PC46    PC47    PC48    PC49
## Standard deviation     0.02559 0.01968 0.01761 0.0163 0.01298 0.01263 0.01171
## Proportion of Variance 0.00001 0.00001 0.00001 0.0000 0.00000 0.00000 0.00000
## Cumulative Proportion  0.99997 0.99998 0.99998 1.0000 0.99999 0.99999 1.00000
##                            PC50     PC51     PC52     PC53     PC54     PC55
## Standard deviation     0.008489 0.006888 0.006081 0.004068 0.003316 0.002259
## Proportion of Variance 0.000000 0.000000 0.000000 0.000000 0.000000 0.000000
## Cumulative Proportion  1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
##                             PC56      PC57      PC58
## Standard deviation     0.0003631 2.072e-06 3.985e-10
## Proportion of Variance 0.0000000 0.000e+00 0.000e+00
## Cumulative Proportion  1.0000000 1.000e+00 1.000e+00
```

```r
# we use 23 Principal Components not the elbow point because we want to maximize the accuracy
pca_df <- as.data.frame(pca_result$x[, 1:23])
pca_df$FHR <- final_previous_merged_updated$FHR
set.seed(222)
train_index <- sample(nrow(pca_df), 0.8 * nrow(pca_df))
train <- pca_df[train_index, ]
test <- pca_df[-train_index, ]

rf_model <- randomForest(FHR ~ ., data = train, ntree = 500, importance = TRUE)
rf_pred <- predict(rf_model, newdata = test)
# RMSE
sqrt(mean((rf_pred - test$FHR)^2))
```

```
## [1] 9.532225
```

```r
print(rf_model)
```

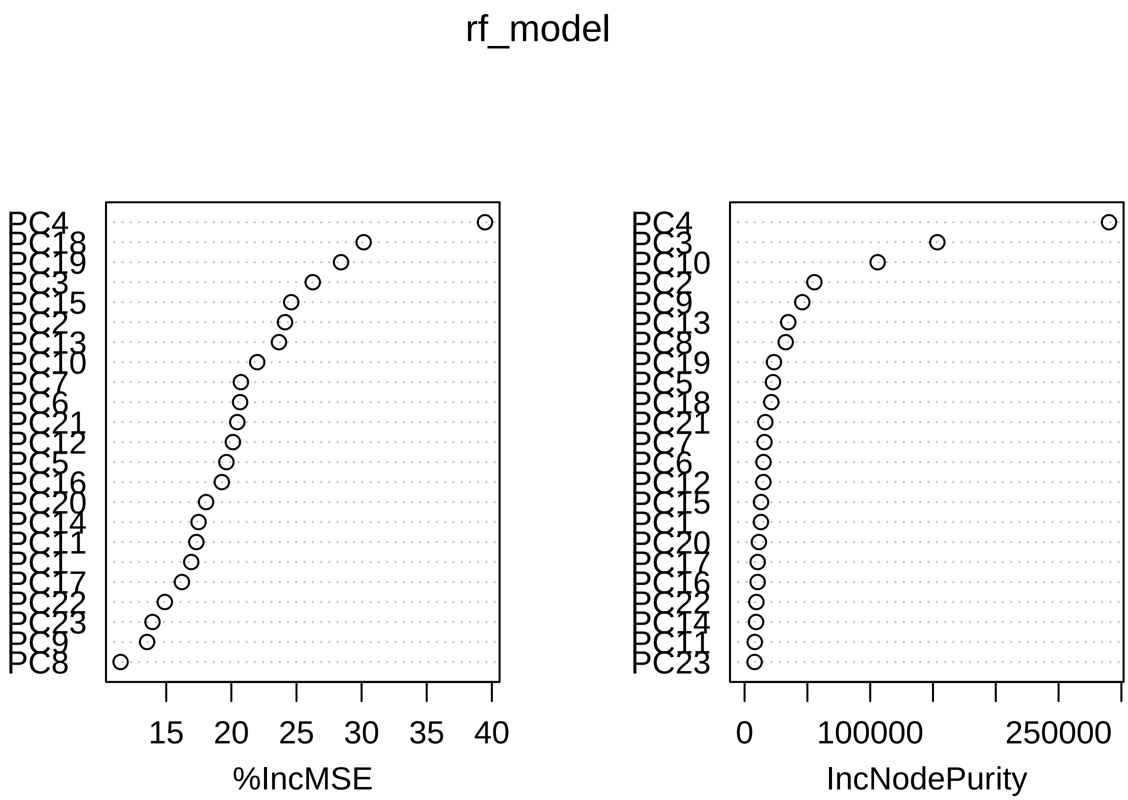
```
##
## Call:
##  randomForest(formula = FHR ~ ., data = train, ntree = 500, importance = TRUE)
##                Type of random forest: regression
##                      Number of trees: 500
```

```
## No. of variables tried at each split: 7
##
##           Mean of squared residuals: 88.03068
##                     % Var explained: 80.84
```

```r
importance(rf_model)
```

```
##       %IncMSE IncNodePurity
## PC1  16.92293     13008.293
## PC2  24.12035     55589.880
## PC3  26.25106    153464.108
## PC4  39.47553    290154.957
## PC5  19.61978     22634.064
## PC6  20.67286     15065.539
## PC7  20.73368     15853.371
## PC8  11.49598     32732.631
## PC9  13.52912     45922.756
## PC10 21.98642    105946.854
## PC11 17.31341      8117.065
## PC12 20.11906     14950.694
## PC13 23.65488     34766.783
## PC14 17.48543      9165.862
## PC15 24.59712     13085.395
## PC16 19.26811     10400.721
## PC17 16.20630     10459.969
## PC18 30.15869     21290.156
## PC19 28.42380     23393.330
## PC20 18.06106     11412.169
## PC21 20.45543     16511.912
## PC22 14.89348      9402.842
## PC23 13.94559      7992.357
```

```r
varImpPlot(rf_model)
```




```
top_pcs <- c("PC4", "PC19", "PC18", "PC3")

actual <- test$FHR
# R^2
ss_res <- sum((actual - rf_pred)^2)            # residual sum of squares
ss_tot <- sum((actual - mean(actual))^2)       # total sum of squares
r_squared <- 1 - (ss_res / ss_tot)
cat("R-squared:", round(r_squared, 4))
```

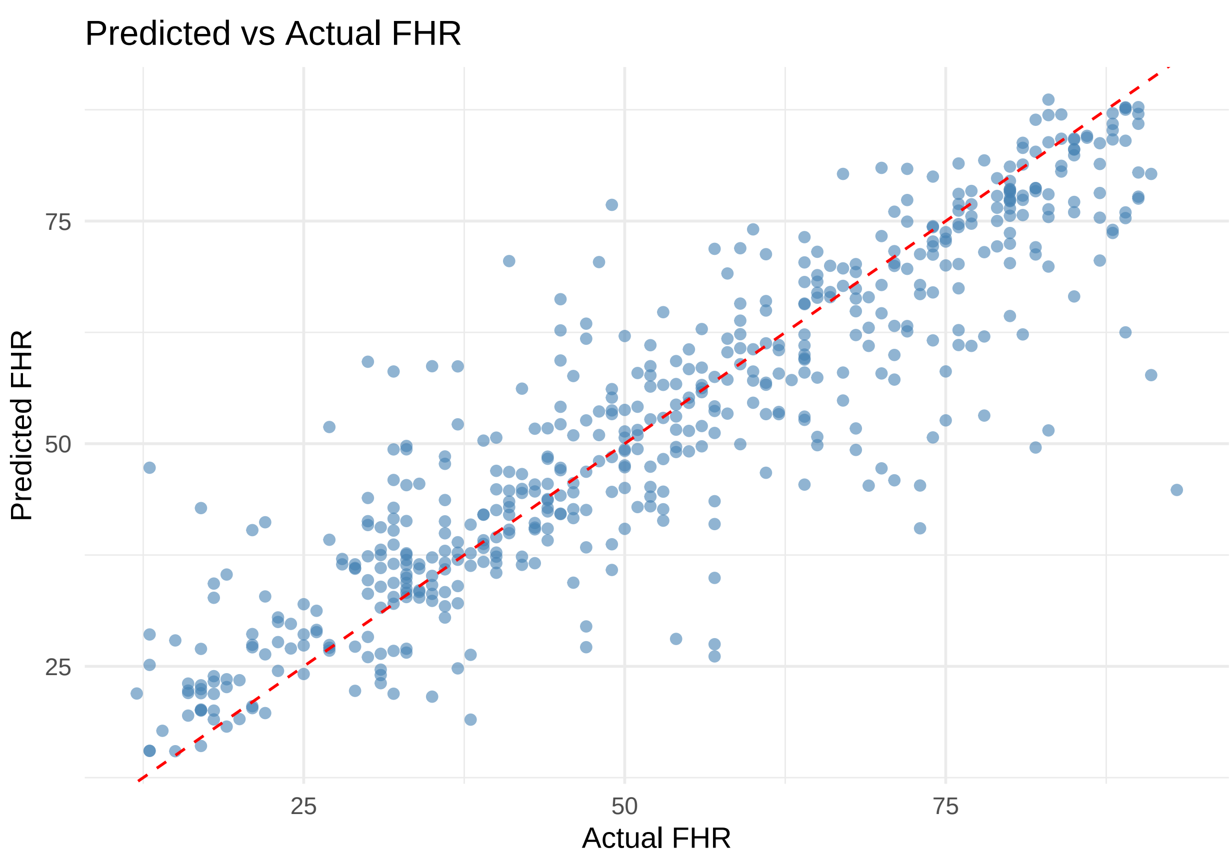
```
## R-squared: 0.7977
```

```
# this table shows how each top 4 components are consisted by different variables
pc_loadings <- pca_result$rotation[, top_pcs]

loading_table <- as.data.frame(pc_loadings) %>%
  tibble::rownames_to_column("Variable") %>%
  tidyr::pivot_longer(cols = all_of(top_pcs), names_to = "PC", values_to = "Loading") %>%
  mutate(abs_loading = abs(Loading)) %>%
  group_by(PC) %>%
  slice_max(order_by = abs_loading, n = 10) %>%   # top 10 per PC
  arrange(PC, desc(abs_loading))

print(loading_table)
```

```
## # A tibble: 40 x 4
```

```
## # Groups:   PC [4]
##    Variable                           PC    Loading abs_loading
##    <chr>                              <chr>   <dbl>       <dbl>
##  1 prev_debitOwnedWithinOneYear       PC18    0.547       0.547
##  2 prev_financialAssets               PC18   -0.464       0.464
##  3 prev_CHS                           PC18    0.365       0.365
##  4 prev_FHR                           PC18   -0.329       0.329
##  5 prev_interestExpense               PC18   -0.271       0.271
##  6 prev_totalCurrentLiabilities       PC18    0.209       0.209
##  7 prev_netProfitAfterTax             PC18   -0.192       0.192
##  8 prev_earningsBeforeInterestAndTax PC18   -0.152       0.152
##  9 prev_totalCurrentAssets            PC18    0.136       0.136
## 10 prev_salesRevenue                  PC18    0.103       0.103
## # i 30 more rows
```

```r
# Show how the prediction fit visually
ggplot(data = NULL, aes(x = test$FHR, y = rf_pred)) +
  geom_point(alpha = 0.6, color = "steelblue") +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
  labs(title = "Predicted vs Actual FHR", x = "Actual FHR", y = "Predicted FHR") +
  theme_minimal()
```



First Random Forest model using PCs shows R^2: 0.7977, RMSE: 9.5322, which shows better than the baseline model.

Random Forest Model using original varaibles

```
set.seed(222)
train_index_og <- sample(nrow(final_previous_merged), 0.8 * nrow(final_previous_merged))
train_og <- final_previous_merged[train_index, ]
test_og <- final_previous_merged[-train_index, ]

rf_model_og <- randomForest(FHR ~ . , data = train_og, ntree = 500, importance = TRUE )
rf_pred_og <- predict(rf_model_og, newdata = test_og)
sqrt(mean((rf_pred_og - test_og$FHR)^2))
```

```
## [1] 9.25811
```

```
print(rf_model_og)
```

```
##
## Call:
##  randomForest(formula = FHR ~ ., data = train_og, ntree = 500,      importance = TRUE)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 20
##
##           Mean of squared residuals: 83.19041
##                     % Var explained: 81.9
```

```
importance(rf_model_og)
```

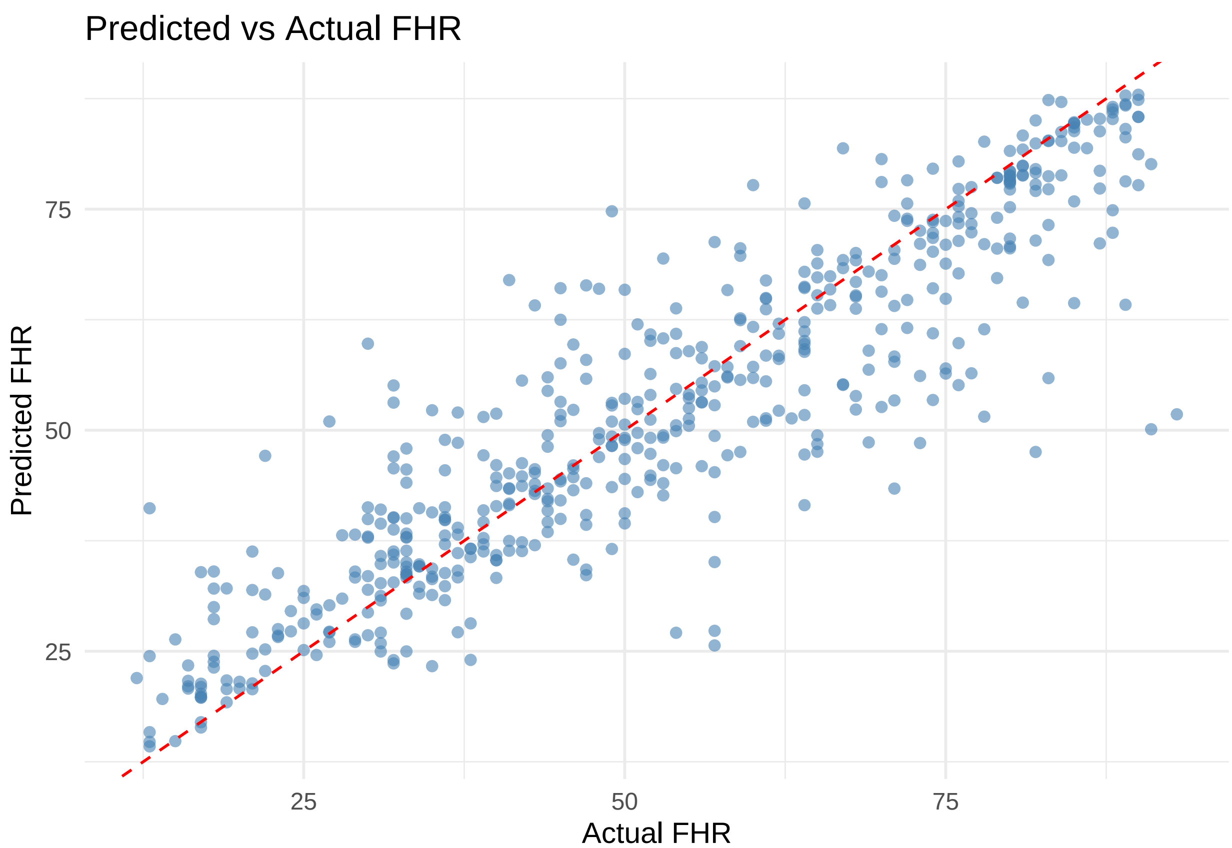
```
##                                           %IncMSE IncNodePurity
## prev_accountsPayable                   9.308327720     3541.2615
## prev_accountsReceivable                9.248558513     2125.5127
## prev_bankCashBalances                 13.008445079     7571.2669
## prev_bankOverdraft                    -0.005458321      391.7992
## prev_debitOwnedWithinOneYear          18.648597761    13888.5646
## prev_financialAssets                  16.084457317     2433.1940
## prev_fixedAssets                      16.943727303     5419.8744
## prev_intangibleAssets                  5.566473542     1223.3378
## prev_otherCurrentAssets                9.705968567     2242.8208
## prev_otherCurrentLiabilities          11.241606519     3385.1347
## prev_otherEquity                       6.818700804     2425.7308
## prev_otherTermAssets                   9.831401130     2449.2562
## prev_otherTermLiabilities              6.330539790     2051.6814
## prev_prepayments                       6.120930180     1874.5921
## prev_retainedEarnings                 10.737086285     8594.9539
## prev_subscribedCapital                 7.444793108     2958.0432
## prev_termLoans                        14.754298075     6979.9985
## prev_totalAssets                      13.271333706     3999.0119
## prev_totalCurrentAssets               13.321986495     4734.6738
## prev_totalCurrentLiabilities          16.717110239     5545.3185
## prev_totalInventories                  8.089459727     3435.2306
## prev_totalLiabilities                 14.155171978     5930.6321
## prev_totalShareholderEquity           17.417624116     9261.8208
```

```
## prev_totalTermAssets                                7.731075545     4245.6430
## prev_totalTermLiabilities                           8.641410088     5421.4275
## prev_accountPayableAccrualFromCashFlow              2.852316231     2784.2598
## prev_capitalExpenditure                             6.651125609     2458.6381
## prev_changeInInventoriesFromCashFlow                6.751559055     3626.7599
## prev_netChangeInCashAndCashEquivalents              3.725022537     1979.6555
## prev_netFundingCashFlow                            13.337838982     4031.7932
## prev_netInvestingCashFlow                          10.318040797     2414.1040
## prev_unbilledAccountsReceivableRevenueFromCashFlow  6.319060513     3421.0791
## prev_currency                                      11.584033088     1397.1752
## prev_financialDate                                 17.570252085     5667.7715
## prev_abnormalItems                                  5.560176895     2715.1482
## prev_amortization                                   6.123388842      977.0644
## prev_companyTaxExpense                             13.481598864     5852.5482
## prev_costOfGoodsSold                                6.055049332     1807.0545
## prev_depreciation                                   7.646646756     2289.5160
## prev_earningsBeforeInterestAndTax                  17.507082981    46202.9883
## prev_grossProfit                                    7.679841443     2013.3835
## prev_interestExpense                               12.348997406     8206.8237
## prev_interestReceived                              13.220295984     2257.9607
## prev_investmentIncome                               6.831936294     2405.0596
## prev_netInvestmentIncome                           10.855509700     9117.2954
## prev_netProfitAfterTax                             16.230487442    75311.0532
## prev_netProfitAfterTaxAndMinorityInterests         10.981971650    19460.9272
## prev_netProfitBeforeTax                            10.022462703    13959.4770
## prev_netSurplus                                    12.163367109    28913.1389
## prev_otherIncome                                    6.157400774     1754.5442
## prev_otherInvestmentExpense                         5.791790694     1466.8958
## prev_otherOperatingExpense                          9.899617165     2669.6444
## prev_totalOperatingExpense                          7.562197221     2866.4843
## prev_totalOperatingRevenue                          9.511350301     1962.9969
## prev_totalStaffCosts                                8.819463304     2374.6334
## prev_salesRevenue                                  14.104758425     4292.6880
## prev_eqyYear                                       12.286862985     3202.4698
## prev_CHS                                           21.543971116   123661.0969
## prev_FHR                                           61.906624692   423542.0335
## prev_X.Other.Currency.to.USD                        9.532094419     2664.3666
## prev_inf_factor                                    13.642213455     2973.6192
## diff_days                                          14.594924249     7507.9784
```

```r
actual_og <- test_og$FHR
ss_res_og <- sum((actual_og - rf_pred_og)^2)
ss_tot_og <- sum((actual_og - mean(actual_og))^2)
r_squared_og <- 1 - (ss_res_og / ss_tot_og)
cat("R-squared:", round(r_squared_og, 4))
```

```
## R-squared: 0.8091
```

```r
# Show how the prediction fit visually
ggplot(data = NULL, aes(x = test_og$FHR, y = rf_pred_og)) +
  geom_point(alpha = 0.6, color = "steelblue") +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
  labs(title = "Predicted vs Actual FHR", x = "Actual FHR", y = "Predicted FHR") +
  theme_minimal()
```



The Random Forest model using the original variables shows R^2: 0.8091, RMSE: 9.2581, which shows better than the Random Forest model using PCs, suggests that we may want to stick to this model rather than use random forest model using PCs.

We will try to use principal components for more models to see if it performs better.

GLM Model using PCs

```
set.seed(222)
model_glm <- glm(FHR ~ ., data = train, family = gaussian)
summary(model_glm)
```

```
##
## Call:
## glm(formula = FHR ~ ., family = gaussian, data = train)
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 52.49156    0.20899 251.167  < 2e-16 ***
## PC1         -0.03111    0.03325  -0.936  0.34963
## PC2          1.07768    0.06391  16.862  < 2e-16 ***
## PC3         -4.27523    0.15044 -28.417  < 2e-16 ***
## PC4         11.30062    0.15225  74.222  < 2e-16 ***
## PC5          3.87515    0.16411  23.613  < 2e-16 ***
## PC6         -2.79336    0.16308 -17.129  < 2e-16 ***
```

```
## PC7          -1.55778    0.18303  -8.511  < 2e-16 ***
## PC8           2.15327    0.19056  11.300  < 2e-16 ***
## PC9          -2.73956    0.21258 -12.887  < 2e-16 ***
## PC10          1.31722    0.18967   6.945 5.06e-12 ***
## PC11         -0.43307    0.22863  -1.894  0.05834 .
## PC12         -1.13578    0.22846  -4.971 7.20e-07 ***
## PC13          0.95164    0.44863   2.121  0.03402 *
## PC14         -0.84169    0.32464  -2.593  0.00959 **
## PC15          0.61832    0.31233   1.980  0.04787 *
## PC16         -0.64194    0.31519  -2.037  0.04181 *
## PC17          0.21135    0.40769   0.518  0.60422
## PC18         -6.58001    0.46871 -14.039  < 2e-16 ***
## PC19         -9.12188    0.49431 -18.454  < 2e-16 ***
## PC20          1.05648    0.57249   1.845  0.06512 .
## PC21          4.31424    0.58258   7.405 1.90e-13 ***
## PC22         -0.62442    0.65655  -0.951  0.34169
## PC23          1.20714    0.81562   1.480  0.13902
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 90.29505)
##
##     Null deviance: 952116  on 2071  degrees of freedom
## Residual deviance: 184924  on 2048  degrees of freedom
## AIC: 15236
##
## Number of Fisher Scoring iterations: 2
```

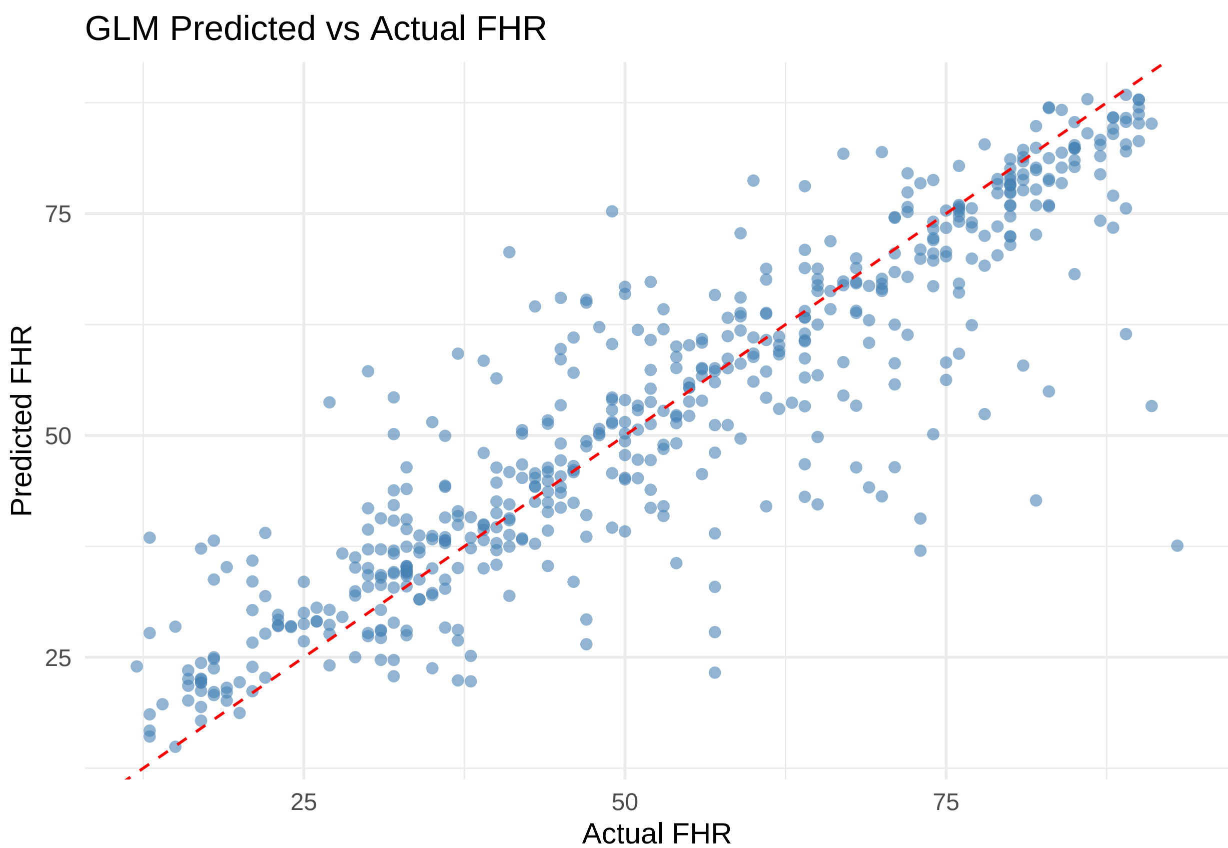
```r
glm_preds <- predict(model_glm, newdata = test)
rmse <- sqrt(mean((glm_preds - test$FHR)^2))
cat("RMSE:", round(rmse, 2))
```

```
## RMSE: 9.51
```

```r
actual <- test$FHR
ss_res2 <- sum((actual - glm_preds)^2)
ss_tot2 <- sum((actual - mean(actual))^2)
r_squared2 <- 1 - (ss_res2 / ss_tot2)
cat("R-squared:", round(r_squared2, 4))
```

```
## R-squared: 0.7988
```

```r
# Show how the prediction fit visually
ggplot(data = NULL, aes(x = test$FHR, y = glm_preds)) +
  geom_point(alpha = 0.6, color = "steelblue") +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
  labs(title = "GLM Predicted vs Actual FHR", x = "Actual FHR", y = "Predicted FHR") +
  theme_minimal()
```



The GLM model using PCs shows R^2: 0.7988, RMSE: 9.51, which can not beat the random forest model using original variables.

Neural Network Model using PCs

```r
set.seed(222)
nn_model <- nnet(FHR ~ ., data = pca_df, size = 5, linout = TRUE)
```

```
## # weights:  126
## initial  value 8406633.917903
## iter  10 value 261667.996904
## iter  20 value 231167.170027
## iter  30 value 227040.640039
## iter  40 value 222663.056038
## iter  50 value 221651.813293
## iter  60 value 220766.718154
## iter  70 value 220489.005995
## iter  80 value 220158.788195
## iter  90 value 219461.476704
## iter 100 value 218279.768828
## final  value 218279.768828
## stopped after 100 iterations
```

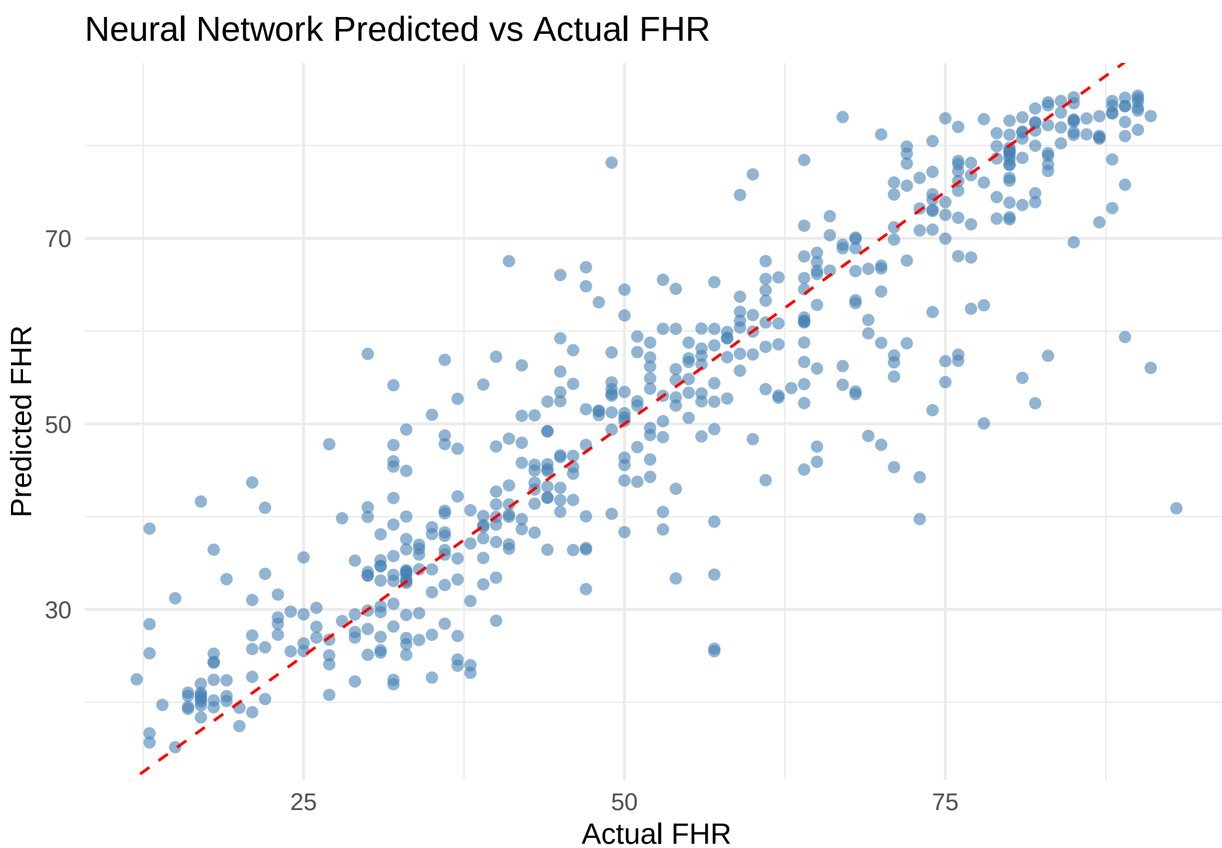
```r
nn_preds <- predict(nn_model, newdata = test)
rmse_nn <- sqrt(mean((nn_preds - test$FHR)^2))
cat("Neural Network RMSE:", round(rmse_nn, 2))
```

```
## Neural Network RMSE: 9.34
```

```r
actual <- test$FHR
ss_res3 <- sum((actual - nn_preds)^2)
ss_tot3 <- sum((actual - mean(actual))^2)
r_squared2 <- 1 - (ss_res3 / ss_tot3)
cat("R-squared:", round(r_squared2, 4))
```

```
## R-squared: 0.8059
```

```r
# Show how the prediction fit visually
ggplot(data = NULL, aes(x = test$FHR, y = nn_preds)) +
  geom_point(alpha = 0.6, color = "steelblue") +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
  labs(title = "Neural Network Predicted vs Actual FHR", x = "Actual FHR", y = "Predicted FHR") +
  theme_minimal()
```



The Neural Network Model shows R^2: 0.8059, RMSE: 9.34, which is still not better than the Random Forest Model using the original variables.

In conclusion, after testing different models using PCs, all those PCR models cannot beat the random forest model as predictive models, thus we may want to use Random Forest Model using the original variables to do the next step.