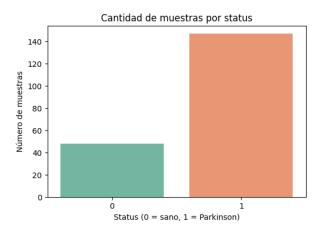
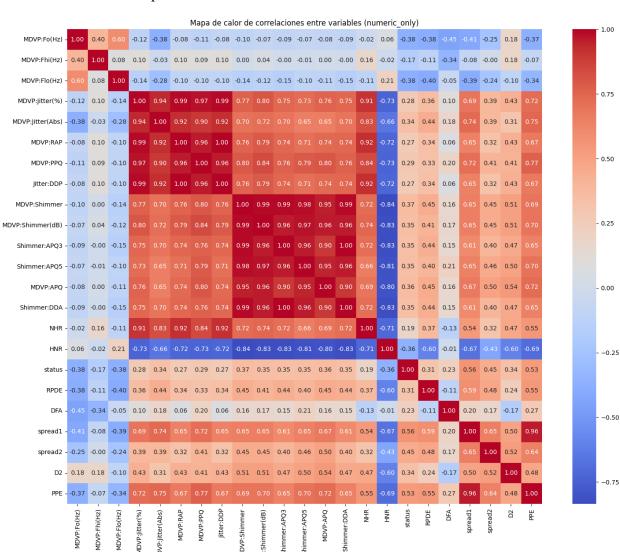
PARKINSON'S PREDICTION

Technical-Statistical Report of the Software

Distribution by Target Status:



Pearson Correlation Map between Variables:



Validation of Assumptions and Statistical Test Selection

It is fundamental to verify the assumptions underlying classical parametric tests. If these assumptions are not met, we opt for non-parametric methods, which are more robust against deviations in distributions.

Normality (Kolmogorov–Smirnov):

For each variable, we divide observations into two groups according to status (0 = healthy, 1 = Parkinson's) and apply the Kolmogorov–Smirnov test separately to each subgroup.

- Null Hypothesis (H₀): Data comes from a normal distribution.
- **Decision:** If $p \ge 0.05$, we do not reject H₀ and consider the sample sufficiently normal. If p < 0.05, we detect significant deviations from normality.

| | Variable | 0 | Normalidad | 1 | Normalidad |
|----|------------------|---------|------------|---------|------------|
| 0 | MDVP:Fo(Hz) | < 0.001 | No normal | < 0.001 | No normal |
| 1 | MDVP:Fhi(Hz) | < 0.001 | No normal | < 0.001 | No normal |
| 2 | MDVP:Flo(Hz) | < 0.001 | No normal | < 0.001 | No normal |
| 3 | MDVP:Jitter(%) | < 0.001 | No normal | < 0.001 | No normal |
| 4 | MDVP:Jitter(Abs) | < 0.001 | No normal | < 0.001 | No normal |
| 5 | MDVP:RAP | < 0.001 | No normal | < 0.001 | No normal |
| 6 | MDVP:PPQ | < 0.001 | No normal | < 0.001 | No normal |
| 7 | Jitter:DDP | < 0.001 | No normal | < 0.001 | No normal |
| 8 | MDVP:Shimmer | < 0.001 | No normal | < 0.001 | No normal |
| 9 | MDVP:Shimmer(dB) | < 0.001 | No normal | < 0.001 | No normal |
| 10 | Shimmer:APQ3 | < 0.001 | No normal | < 0.001 | No normal |
| 11 | Shimmer:APQ5 | < 0.001 | No normal | < 0.001 | No normal |
| 12 | MDVP:APQ | 0.015 | No normal | < 0.001 | No normal |
| 13 | Shimmer:DDA | < 0.001 | No normal | < 0.001 | No normal |
| 14 | NHR | < 0.001 | No normal | < 0.001 | No normal |
| 15 | HNR | 0.013 | No normal | 0.002 | No normal |
| 16 | RPDE | 0.630 | Normal | < 0.001 | No normal |
| 17 | DFA | < 0.001 | No normal | 0.090 | Normal |
| 18 | spread1 | 0.371 | Normal | 0.009 | No normal |
| 19 | spread2 | 0.640 | Normal | 0.520 | Normal |

| 20 | D2 | 0.917 | Normal | 0.025 | No normal |
|----|-----|-------|-----------|---------|-----------|
| 21 | PPE | 0.030 | No normal | < 0.001 | No normal |

Homogeneity of Variances (Levene):

Even if both samples are normal, parametric tests such as ANOVA require similar variances across groups. With the Levene test we verify:

- **Ho:** Variances are equal across groups.
- **Decision:** $p \ge 0.05 \rightarrow$ homogeneous variances; $p < 0.05 \rightarrow$ unequal variances.

Choice of Statistical Test:

Based on results from normality and homogeneity tests:

- If both groups pass Shapiro ($p \ge 0.05$) and Levene ($p \ge 0.05$), we use the ANOVA-F test. The F-statistic measures the ratio between inter-group variability and intragroup variability; a higher value indicates more discriminative power.
- Otherwise, we apply the Kruskal–Wallis test, which does not assume normality nor equal variances. Its p-value indicates if medians significantly differ between the groups.

| | Variable | Prueba | Estadístico | p-valor |
|----|------------------|----------------|-------------|---------|
| 1 | spread2 | ANOVA-F | 50.34 | < 0.001 |
| 2 | PPE | Kruskal–Wallis | 68.08 | < 0.001 |
| 3 | spread1 | Kruskal–Wallis | 68.08 | < 0.001 |
| 4 | MDVP:APQ | Kruskal–Wallis | 45.88 | < 0.001 |
| 5 | MDVP:Jitter(Abs) | Kruskal–Wallis | 36.87 | < 0.001 |
| 6 | MDVP:PPQ | Kruskal–Wallis | 35.63 | < 0.001 |
| 7 | MDVP:Shimmer(dB) | Kruskal–Wallis | 35.11 | < 0.001 |
| 8 | MDVP:Shimmer | Kruskal–Wallis | 34.53 | < 0.001 |
| 9 | MDVP:Jitter(%) | Kruskal–Wallis | 33.32 | < 0.001 |
| 10 | Jitter:DDP | Kruskal–Wallis | 33.25 | < 0.001 |
| 11 | MDVP:RAP | Kruskal–Wallis | 33.13 | < 0.001 |
| 12 | NHR | Kruskal–Wallis | 32.24 | < 0.001 |
| 13 | Shimmer:APQ5 | Kruskal–Wallis | 31.47 | < 0.001 |
| 14 | Shimmer:APQ3 | Kruskal–Wallis | 28.05 | < 0.001 |
| 15 | Shimmer:DDA | Kruskal–Wallis | 28.02 | < 0.001 |

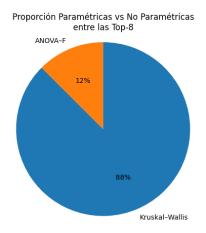
| 16 | HNR | Kruskal–Wallis | 24.46 | < 0.001 |
|----|--------------|----------------|-------|---------|
| 17 | D2 | Kruskal–Wallis | 21.85 | < 0.001 |
| 18 | RPDE | Kruskal–Wallis | 18.55 | < 0.001 |
| 19 | MDVP:Fo(Hz) | Kruskal–Wallis | 17.40 | <0.001 |
| 20 | MDVP:Flo(Hz) | Kruskal–Wallis | 16.81 | < 0.001 |
| 21 | MDVP:Fhi(Hz) | Kruskal–Wallis | 13.21 | <0.001 |
| 22 | DFA | Kruskal–Wallis | 9.69 | 0.002 |

For parametric variables (those passing Shapiro–Wilk and Levene), we use the F-statistic from ANOVA.

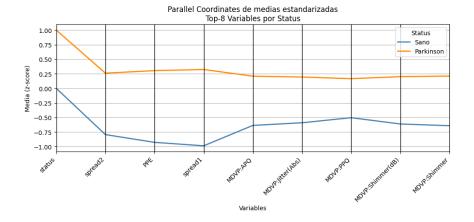
- Mathematically, F = (between-groups variability) / (within-group variability).
- A higher F-value indicates a greater relative difference in means between healthy and Parkinson's groups, making the variable more discriminative.

For non-parametric variables (those failing assumptions), we use the H-statistic from Kruskal-Wallis.

- H measures dispersion in ranks of observations between groups.
- A higher H-value indicates a greater difference in distributions between the two samples.



After ranking variables, we selected the eight most discriminative features, standardized them to z-scores to equalize scales, and calculated their means for each group (healthy vs. Parkinson's). We then plotted a parallel coordinate graph, where the Parkinson's line (orange) consistently appears above the healthy line (blue) across these eight variables, notably showing the largest separation between groups in the spread2 and spread1 variables.



Training:

We applied an 80% hold-out of the data for training and 20% for testing.

Cross-validation Table (CV):

The table lists each model's average training time (TrainTime) and evaluation metrics (Accuracy, Precision, Recall, F1, and MCC), averaged across a 5-fold Stratified CV scheme. The models are sorted by MCC in descending order to highlight the model with the best balanced classification capability between classes.

| Modelo | Tiempo (s) | Accuracy | Precision | Recall | F1 | MCC |
|---------------|------------|----------|-----------|--------|------|------|
| Random Forest | 0.58 | 0.85 | 0.89 | 0.92 | 0.9 | 0.59 |
| Naïve Bayes | 0.01 | 0.76 | 0.97 | 0.71 | 0.82 | 0.54 |
| XGBoost | 0.12 | 0.83 | 0.89 | 0.88 | 0.88 | 0.54 |
| k-NN | 0.01 | 0.81 | 0.87 | 0.88 | 0.87 | 0.47 |
| SVM (RBF) | 0.01 | 0.82 | 0.85 | 0.93 | 0.89 | 0.46 |
| Logistic L2 | 0.02 | 0.81 | 0.85 | 0.91 | 0.88 | 0.44 |

System Characteristics Table:

Describes the environment where experiments were performed: operating system, processor, and RAM. This provides context regarding training times and ensures reproducibility of results.

| Recurso | Especificación |
|---------|----------------|
| OS | Linux 6.1.123+ |
| CPU | x86_64 |
| RAM | 12.67 GB |

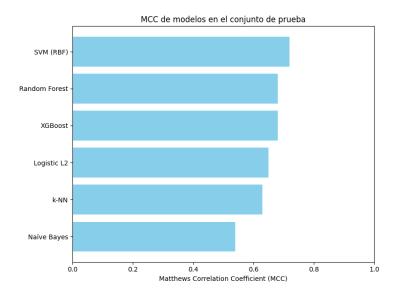
Testing:

In the final phase, we trained each complete pipeline using 80% of data, serialized it to disk for reproducibility, and evaluated its performance on the remaining 20% ("test set"). For each model, we calculated Accuracy, Precision, Recall, F1, and MCC, and plotted its confusion matrix as an annotated heatmap with True/False Positives/Negatives. Finally, all metrics were gathered into a table sorted by MCC, reflecting overall class balance.

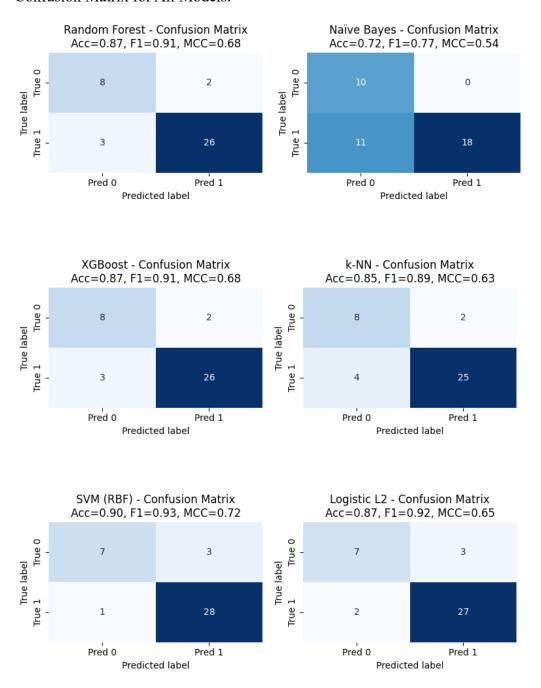
| Modelo | Nombre archivo | Accuracy | Precision | Recall | F1 | MCC |
|---------------|-----------------|----------|-----------|--------|------|------|
| SVM (RBF) | SVM_(RBF).h | 0.9 | 0.9 | 0.97 | 0.93 | 0.72 |
| Random Forest | Random_Forest.h | 0.87 | 0.93 | 0.9 | 0.91 | 0.68 |
| XGBoost | XGBoost.h | 0.87 | 0.93 | 0.9 | 0.91 | 0.68 |
| Logistic L2 | Logistic_L2.h | 0.87 | 0.9 | 0.93 | 0.92 | 0.65 |
| k-NN | k-NN.h | 0.85 | 0.93 | 0.86 | 0.89 | 0.63 |
| Naïve Bayes | Naïve_Bayes.h | 0.72 | 1.0 | 0.62 | 0.77 | 0.54 |

Matthews Correlation Coefficient (MCC):

MCC is a correlation metric for binary classification that takes into account TP, TN, FP, and FN, providing a single interpretable value (ranging from -1 to +1). It was selected as the primary criterion because it balances prediction effectiveness in datasets with potential class imbalance.



Confusion Matrix for All Models:



In the final stage, we selected the best-performing model according to MCC on the test set (in this case, SVM with RBF kernel, MCC = 0.720), and saved its pipeline. To verify proper functionality, we loaded the pipeline and performed a test inference on a sample from the test set, obtaining both predicted labels and associated probabilities.

To confirm that its superiority was not due to chance, we applied the McNemar test between the best model and each of the other models: constructing contingency tables based on their predictions on the same test set, calculating the p-value, and determining if differences in the number of correct/incorrect predictions were statistically significant ($\alpha = 0.05$).

McNemar Test (Best vs. Others):

- SVM (RBF) vs Random Forest: p-value = $0.250 \rightarrow \text{significant difference}$: No
- SVM (RBF) vs XGBoost: p-value = $0.375 \rightarrow \text{significant difference}$: No
- SVM (RBF) vs Logistic L2: p-value = $1.000 \rightarrow \text{significant difference}$: No
- SVM (RBF) vs k-NN: p-value = $0.219 \rightarrow \text{significant difference}$: No
- SVM (RBF) vs Naïve Bayes: p-value = $0.000 \rightarrow \text{significant difference}$: Yes

Hyperparameter Optimization:

We applied GridSearchCV with stratified 5-fold cross-validation (same as previously) for each key metric: AUC-ROC, Accuracy, Precision, Recall, F1, and MCC.

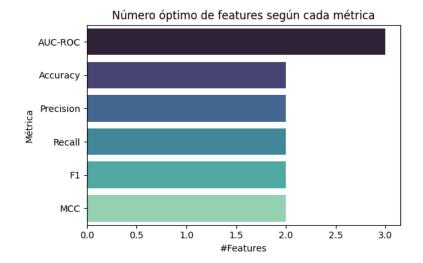
| Métricas | Parámetros | CV_score |
|-----------|--|----------|
| AUC-ROC | {'clf_C': 0.1, 'clf_gamma': 'scale', 'clf_kernel': 'linear'} | 0.90 |
| Accuracy | {'clf_C': 100, 'clf_gamma': 1, 'clf_kernel': 'rbf'} | 0.84 |
| Precision | {'clf_C': 100, 'clf_gamma': 1, 'clf_kernel': 'rbf'} | 0.88 |
| Recall | {'clf_C': 0.1, 'clf_gamma': 'scale', 'clf_kernel': 'rbf'} | 1.0 |
| F1 | {'clf_C': 1, 'clf_gamma': 1, 'clf_kernel': 'rbf'} | 0.89 |
| MCC | {'clf_C': 100, 'clf_gamma': 1, 'clf_kernel': 'rbf'} | 0.56 |

Optimization by MCC and Feature Selection with RFECV:

To refine our SVM, we performed two sequential steps:

- 1. GridSearchCV optimizing the MCC metric (Matthews Correlation Coefficient), balancing true/false positives and negatives.
- 2. RFECV with linear SVM to determine the optimal number of features for each metric (AUC-ROC, Accuracy, Precision, Recall, F1, and MCC).

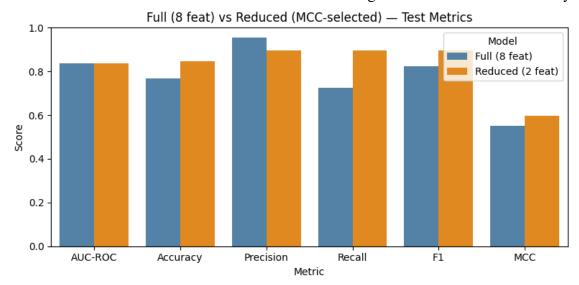
| Métrica | #Features | CV_Score | Test_Score | Features |
|-------------|-----------|----------|------------|---------------------------------|
| AUC- ROC | 3 | 0.912 | 0.921 | spread1, MDVP:APQ, MDVP:Shimmer |
| Accuracy | 2 | 0.847 | 0.846 | MDVP:APQ, MDVP:Shimmer |
| Precision | 2 | 0.876 | 0.897 | MDVP:APQ, MDVP:Shimmer |
| Recall | 2 | 0.933 | 0.897 | MDVP:APQ, MDVP:Shimmer |
| F1 | 2 | 0.902 | 0.897 | MDVP:APQ, MDVP:Shimmer |
| MCC | 2 | 0.573 | 0.597 | MDVP:APQ, MDVP:Shimmer |



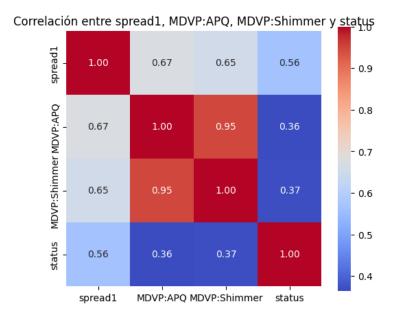
Comparativa de rendimiento en Test: Full (8 features) vs Reduced (2 features)

| Modelo | AUC-ROC | Accuracy | Precision | Recall | F1 | MCC |
|------------------|---------|----------|-----------|--------|-------|-------|
| Full (8 feat) | 0.838 | 0.769 | 0.955 | 0.724 | 0.824 | 0.55 |
| Reduced (2 feat) | 0.838 | 0.846 | 0.897 | 0.897 | 0.897 | 0.597 |

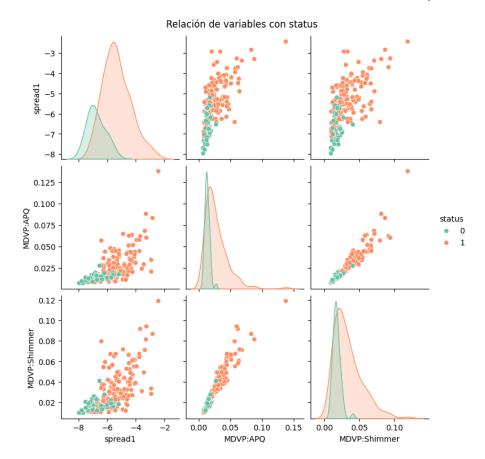
Reducing the feature set to just MDVP:APQ and MDVP:Shimmer not only simplifies the model by reducing variables by 75%, but also enhances its balanced classification capability, reflected in increased MCC. This confirms that these two features capture most of the discriminative information without sacrificing overall classifier reliability.



Correlation Map of Final Variables by Status:



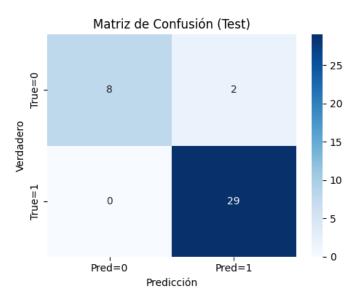
Discrimination of Variables between Patients with Parkinson's vs. Healthy Individuals:



Using the final optimized model (SVM-RBF optimized by MCC) trained on the three final variables (spread1, MDVP:APQ, and MDVP:Shimmer):**finales** (spread1, MDVP:APQ y MDVP:Shimmer):

| Métrica | Train | Test |
|-----------|-------|-------|
| AUC-ROC | 0.951 | 0.921 |
| Accuracy | 0.885 | 0.949 |
| Precision | 0.879 | 0.935 |
| Recall | 0.983 | 1.0 |
| F1 | 0.928 | 0.967 |
| MCC | 0.669 | 0.865 |

Final Confusion Matrix:



Hybrid Model Selection:

| Model | Auc | Accuracy | Precision | Recall | F1 | Mcc |
|-----------------------|-------|----------|-----------|--------|-------|-------|
| Soft_voting_parkinson | 0.917 | 0.846 | 0.897 | 0.897 | 0.897 | 0.597 |
| Stacking_parkinson | 0.914 | 0.821 | 0.867 | 0.897 | 0.881 | 0.515 |