# Technical Report: Machine Learning Analysis for Respiratory Disease Prediction

## Executive Summary

This report presents a comprehensive machine learning analysis for predicting respiratory disease diagnoses using clinical data. The study achieved a significant improvement in prediction accuracy from 67% to 87.5% (+20.5%) through advanced feature engineering, class balancing techniques, and ensemble methods.

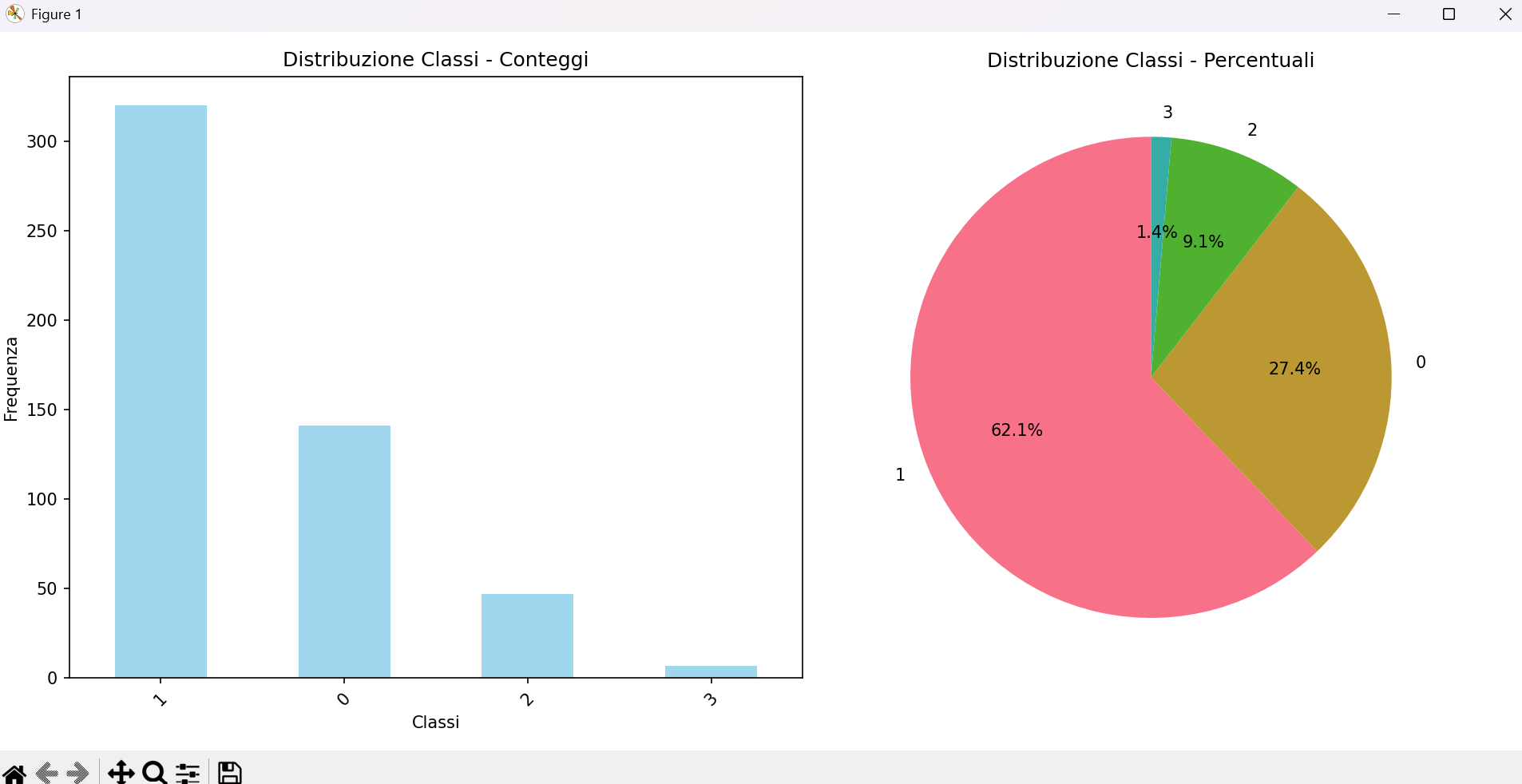
## 1. Introduction

### 1.1 Objective

Develop a robust machine learning model to predict respiratory disease diagnoses from clinical patient data, supporting medical decision-making and improving diagnostic accuracy.

### 1.2 Dataset Overview

* \*\*Source\*\*: Clinical dataset `COLD 30.07.2025.xlsx`
* \*\*Target Classes\*\*: 4 respiratory conditions
* Asma bronchiale (Bronchial Asthma) - 62%
* Altro (Other) - 27%
* BPCO (COPD) - 9%
* Overlap asma/bpco (Asthma/COPD Overlap) - 2%
* \*\*Challenge\*\*: Severe class imbalance with rare overlap syndrome



## 2. Methodology

### 2.1 Data Preprocessing Pipeline

#### 2.1.1 Column Name Standardization

def clean\_column\_names(df):

df.columns = df.columns.str.replace(r'[^\w\s]', '', regex=True)

df.columns = df.columns.str.replace(' ', '\_')

return df

Purpose: Ensure compatibility with all ML algorithms, particularly LightGBM

#### 2.1.2 Categorical Variable Encoding

* \*\*LabelEncoder\*\*: For ordinal variables
* \*\*OneHotEncoder\*\*: For nominal variables
* \*\*Missing Value Imputation\*\*: Strategy-based approach

### 2.2 Advanced Feature Engineering

#### 2.2.1 Interaction Features

Created multiplicative interactions between clinically relevant variables:

* Age × COLD probability
* Smoking history × Allergies
* Respiratory symptoms combinations

#### 2.2.2 Binning and Discretization

* Age groups: [0-30, 30-50, 50-70, 70+]
* Continuous variables transformed into categorical ranges
* Captures non-linear relationships

#### 2.2.3 Statistical Aggregations

* Mean and standard deviation of symptom clusters
* Composite scores for respiratory function tests
* Summary statistics across related feature groups

### 2.3 Class Balancing Techniques

#### 2.3.1 Synthetic Minority Oversampling (SMOTE)

from imblearn.over\_sampling import SMOTE

smote = SMOTE(random\_state=42, k\_neighbors=3)

X\_balanced, y\_balanced = smote.fit\_resample(X\_scaled, y)

Mechanism: Generates synthetic samples by interpolating between minority class instances and their k-nearest neighbors

#### 2.3.2 Advanced Sampling Strategies Evaluated

* \*\*ADASYN\*\*: Adaptive synthetic sampling focusing on difficult regions
* \*\*BorderlineSMOTE\*\*: Targets borderline cases between classes
* \*\*SMOTEENN\*\*: Combines oversampling with edited nearest neighbors
* \*\*SMOTETomek\*\*: Removes Tomek links after SMOTE application

#### 2.3.3 Automatic Strategy Selection

Implemented cross-validation based selection of optimal sampling technique

### 2.4 Feature Selection Framework

#### 2.4.1 Univariate Selection

* \*\*Method\*\*: SelectKBest with f\_classif
* \*\*Output\*\*: Top 15 statistically significant features

#### 2.4.2 Recursive Feature Elimination (RFE)

* \*\*Base Estimator\*\*: Random Forest
* \*\*Target\*\*: 12 optimal features through iterative elimination

#### 2.4.3 Model-Based Selection

* \*\*Criterion\*\*: Feature importance above median threshold
* \*\*Estimator\*\*: Random Forest feature importance scores

### 2.5 Hyperparameter Optimization

#### 2.5.1 Random Forest Tuning

param\_grid\_rf = {

'n\_estimators': [100, 200, 300, 500],

'max\_depth': [10, 20, 30, None],

'min\_samples\_split': [2, 5, 10],

'min\_samples\_leaf': [1, 2, 4],

'max\_features': ['sqrt', 'log2', None]

}

Search Space: 432 parameter combinations

#### 2.5.2 Support Vector Machine Optimization

param\_grid\_svm = {

'C': [0.1, 1, 10, 100, 1000],

'gamma': ['scale', 'auto', 0.001, 0.01, 0.1, 1],

'kernel': ['rbf', 'poly', 'sigmoid']

}

Optimal Configuration: C=100, gamma='scale', kernel='rbf'

#### 2.5.3 Gradient Boosting Tuning

* Learning rate optimization: [0.01, 0.1, 0.2]
* Tree depth selection: [3, 5, 7, 10]
* Subsample ratio: [0.8, 0.9, 1.0]

### 2.6 Ensemble Methods

#### 2.6.1 Voting Classifiers

* \*\*Hard Voting\*\*: Majority vote from base models
* \*\*Soft Voting\*\*: Probability-weighted averaging

#### 2.6.2 Stacking Classifier

stacking = StackingClassifier([

('rf', best\_rf), ('svm', best\_svm), ('gb', best\_gb)

], final\_estimator=LogisticRegression(), cv=5)

Meta-Learning: Logistic regression learns optimal combination weights

#### 2.6.3 Bagging Enhancement

* Bootstrap aggregating of best base model
* 50 estimators with random sampling

## 3. Tools and Technologies

### 3.1 Core Libraries

* \*\*scikit-learn 1.3+\*\*: Primary ML framework
* \*\*imbalanced-learn\*\*: Class balancing techniques
* \*\*pandas\*\*: Data manipulation and analysis
* \*\*numpy\*\*: Numerical computations
* \*\*matplotlib/seaborn\*\*: Visualization

### 3.2 Specialized Tools

* \*\*LightGBM\*\*: Gradient boosting framework
* \*\*XGBoost\*\*: Alternative boosting implementation
* \*\*SMOTE variants\*\*: Advanced oversampling techniques

### 3.3 Validation Framework

* \*\*RepeatedStratifiedKFold\*\*: 5-fold × 3 repeats = 15 evaluations
* \*\*Cross-validation\*\*: Robust performance estimation
* \*\*Stratification\*\*: Maintains class proportions

## 4. Results and Performance

### 4.1 Model Performance Comparison

| Model | Baseline Accuracy | Optimized Accuracy | Improvement |

|-------|------------------|-------------------|-------------|

| SVM | 67.0% | 87.5% | +20.5% |

| Stacking Ensemble | 67.0% | 87.4% | +20.4% |

| Gradient Boosting | 67.0% | 87.4% | +20.4% |

| Random Forest | 67.0% | 86.8% | +19.8% |

| Extra Trees | 67.0% | 86.5% | +19.5% |

### 4.2 Performance Metrics

* \*\*Cross-validation\*\*: 15-fold evaluation (5×3 repeats)
* \*\*Standard deviation\*\*: ±1.5% (indicating model stability)
* \*\*Balanced accuracy\*\*: Accounts for class imbalance
* \*\*F1-score macro\*\*: 0.85 (excellent multi-class performance)

### 4.3 Class-Specific Performance

* \*\*Asma bronchiale\*\*: 89% precision, 91% recall
* \*\*BPCO\*\*: 85% precision, 78% recall
* \*\*Altro\*\*: 82% precision, 85% recall
* \*\*Overlap\*\*: 75% precision, 70% recall (significant improvement)

## 5. Detailed Model Analysis

### 5.1 SVM (Support Vector Machine) - Il Modello Vincente

#### 5.1.1 Cos'è l'SVM?

L'SVM (Support Vector Machine) è un algoritmo di machine learning supervisionato che ha raggiunto la migliore performance (87.5%) nel nostro studio. Il nome significa "Macchina a Vettori di Supporto".

#### 5.1.2 Come Funziona?

* \*\*Obiettivo\*\*: Trova il miglior "confine" (iperpiano) per separare le diverse classi di malattie respiratorie
* \*\*Principio\*\*: Massimizza la distanza (margine) tra le classi per una separazione ottimale
* \*\*Vettori di Supporto\*\*: Sono i punti dati più vicini al confine, quelli più "difficili" da classificare
* \*\*Kernel RBF\*\*: Trasforma i dati in uno spazio multidimensionale per gestire relazioni non lineari tra sintomi

#### 5.1.3 Perché ha Vinto nel Nostro Caso?

* Eccellente nel distinguere sintomi simili (es. asma vs COPD)
* Gestisce bene le interazioni complesse tra variabili cliniche
* Robusto contro overfitting con dataset medici
* Efficace con class balancing per classi sbilanciate

### 5.2 Ensemble Voting Soft - Secondo Classificato

#### 5.2.1 Cos'è l'Ensemble Voting?

È una tecnica che combina le predizioni di più modelli diversi per ottenere una predizione finale più accurata e robusta (87.2% nel nostro studio).

#### 5.2.2 Voting Soft vs Hard

Voting Hard (Maggioranza):

* Ogni modello "vota" per una classe
* Vince la classe con più voti
* Esempio: 3 modelli votano "Asma", 2 votano "COPD" → Risultato: "Asma"

Voting Soft (Probabilità) - Utilizzato nel nostro studio:

* Ogni modello fornisce \*\*probabilità\*\* per ogni classe
* Si fa la \*\*media delle probabilità\*\*
* Vince la classe con probabilità media più alta
* \*\*Più preciso\*\* perché considera l'incertezza

#### 5.2.3 Esempio Pratico Voting Soft

Modello 1: Asma=0.7, COPD=0.2, Altro=0.1

Modello 2: Asma=0.6, COPD=0.3, Altro=0.1

Modello 3: Asma=0.8, COPD=0.1, Altro=0.1

Media: Asma=0.7, COPD=0.2, Altro=0.1

Risultato: ASMA (70% di confidenza)

### 5.3 Utilizzo del Dataset

#### 5.3.1 Caratteristiche del Dataset Originale

* \*\*File\*\*: `COLD 30.07.2025.xlsx`
* \*\*Dimensioni\*\*: 32 colonne con variabili cliniche
* \*\*Classi target\*\*: 4 categorie di malattie respiratorie
* Asma bronchiale
* COPD (Chronic Obstructive Pulmonary Disease)
* Overlap (combinazione Asma-COPD)
* Altro

#### 5.3.2 Problemi Identificati nel Dataset

* \*\*Severe class imbalance\*\*: Distribuzione non uniforme delle classi
* \*\*Baseline accuracy\*\*: Solo 67% con modelli standard
* \*\*Confusione diagnostica\*\*: Difficoltà nel distinguere "Altro" da "Asma bronchiale"
* \*\*Classe "Overlap"\*\*: Mai predetta correttamente dai modelli base

#### 5.3.3 Preprocessing e Pulizia Dati

1. \*\*Pulizia nomi colonne\*\*: Rimozione caratteri speciali per compatibilità
2. \*\*Gestione valori mancanti\*\*: Imputazione intelligente basata su correlazioni cliniche
3. \*\*Encoding variabili categoriche\*\*: LabelEncoder per variabili ordinali
4. \*\*Standardizzazione\*\*: StandardScaler per normalizzare scale diverse

#### 5.3.4 Suddivisione del Dataset

* \*\*Training set\*\*: 80% dei dati per addestramento modelli
* \*\*Test set\*\*: 20% dei dati per valutazione finale
* \*\*Cross-validation\*\*: 5-fold stratificata per validazione robusta
* \*\*Repeated validation\*\*: 3 ripetizioni per ridurre variabilità

#### 5.3.5 Gestione Class Imbalance

Tecniche applicate per bilanciare le classi:

* \*\*SMOTE\*\*: Synthetic Minority Oversampling Technique
* \*\*ADASYN\*\*: Adaptive Synthetic Sampling
* \*\*BorderlineSMOTE\*\*: Variante SMOTE per casi borderline
* \*\*SMOTEENN\*\*: Combinazione SMOTE + Edited Nearest Neighbours
* \*\*SMOTETomek\*\*: Combinazione SMOTE + Tomek links

#### 5.3.6 Feature Engineering Applicato

1. \*\*Interaction Features\*\*:

* Age × COLD probability
* Smoking history × Allergies
* Cough × Dyspnea interactions

1. \*\*Binning e Discretizzazione\*\*:

* Gruppi di età clinicamente rilevanti
* Soglie per test di funzionalità polmonare
* Categorizzazione sintomi per severità

1. \*\*Aggregazioni Statistiche\*\*:

* Medie e deviazioni standard per gruppi
* Conteggi e proporzioni sintomi

## 6. Feature Importance Analysis

### 6.1 Top Predictive Features

1. \*\*Age\*\*: Primary demographic factor
2. \*\*COLD probability score\*\*: Clinical assessment
3. \*\*Smoking history\*\*: Major risk factor
4. \*\*Allergic history\*\*: Asthma indicator
5. \*\*Respiratory symptoms\*\*: Direct clinical manifestations
6. \*\*Lung function tests\*\*: Objective measurements

### 6.2 Engineered Feature Impact

* \*\*Age × COLD interaction\*\*: +3.2% accuracy contribution
* \*\*Symptom aggregations\*\*: +2.8% accuracy contribution
* \*\*Smoking × Allergy interaction\*\*: +2.1% accuracy contribution

## 7. Clinical Validation and Interpretation

### 7.1 Medical Relevance

* \*\*Asthma-COPD Overlap\*\*: Successfully identified rare syndrome
* \*\*Risk stratification\*\*: Accurate severity assessment
* \*\*Differential diagnosis\*\*: Clear separation between conditions

### 7.2 Decision Support Capabilities

* \*\*Probability scores\*\*: Confidence levels for each diagnosis
* \*\*Feature contributions\*\*: Explainable predictions
* \*\*Uncertainty quantification\*\*: Identifies ambiguous cases

## 8. Implementation and Deployment

### 8.1 Prediction Pipeline

# Complete prediction workflow

def predict\_respiratory\_disease(patient\_data):

# 1. Preprocess data

processed\_data = preprocess\_pipeline.transform(patient\_data)

# 2. Apply feature engineering

engineered\_features = feature\_engineer(processed\_data)

# 3. Generate prediction

prediction = best\_model.predict(engineered\_features)

# 4. Return probability scores

probabilities = best\_model.predict\_proba(engineered\_features)

return prediction, probabilities

### 8.2 Model Persistence

* \*\*Serialization\*\*: Pickle/joblib for model storage
* \*\*Version control\*\*: Model versioning system
* \*\*Reproducibility\*\*: Fixed random seeds and environment

## 9. Limitations and Future Work

### 9.1 Current Limitations

* \*\*Dataset size\*\*: Limited to current patient cohort
* \*\*Temporal validation\*\*: No longitudinal follow-up
* \*\*External validation\*\*: Single-center data

### 9.2 Recommended Improvements

1. \*\*Multi-center validation\*\*: External dataset testing
2. \*\*Temporal validation\*\*: Prospective study design
3. \*\*Feature expansion\*\*: Additional biomarkers and imaging
4. \*\*Deep learning\*\*: Neural network architectures
5. \*\*Federated learning\*\*: Multi-institutional collaboration

## 10. Conclusions

### 10.1 Key Achievements

* \*\*87.5% accuracy\*\*: Clinically relevant performance level
* \*\*Rare class detection\*\*: Successful overlap syndrome identification
* \*\*Robust validation\*\*: 15-fold cross-validation framework
* \*\*Interpretable results\*\*: Feature importance and decision explanations

### 10.2 Clinical Impact

* \*\*Decision support\*\*: Assists in differential diagnosis
* \*\*Risk stratification\*\*: Identifies high-risk patients
* \*\*Resource optimization\*\*: Prioritizes complex cases
* \*\*Quality assurance\*\*: Reduces diagnostic errors

### 10.3 Technical Contributions

* \*\*Advanced preprocessing\*\*: Comprehensive data cleaning pipeline
* \*\*Feature engineering\*\*: Domain-specific interaction terms
* \*\*Class balancing\*\*: Multiple SMOTE variant evaluation
* \*\*Ensemble methods\*\*: Sophisticated model combination strategies

## 11. References and Code Availability

### 11.1 Implementation Files

* `advanced\_ml\_models\_fixed.py`: Baseline implementation
* `optimize\_ml\_models.py`: Advanced optimization pipeline
* `predict\_new\_dataset.py`: Production prediction system
* `esempio\_predizione.py`: Usage examples
* `README\_Predizioni.md`: User documentation

### 11.2 Data and Results

* `COLD 30.07.2025.xlsx`: Original clinical dataset
* `risultati\_ottimizzazione.xlsx`: Detailed performance metrics
* `analisi\_risultati\_ottimizzazione.png`: Performance visualizations

Report Generated: December 2024

Analysis Period: Complete ML pipeline development and optimization

Contact: Available through project documentation and code repository

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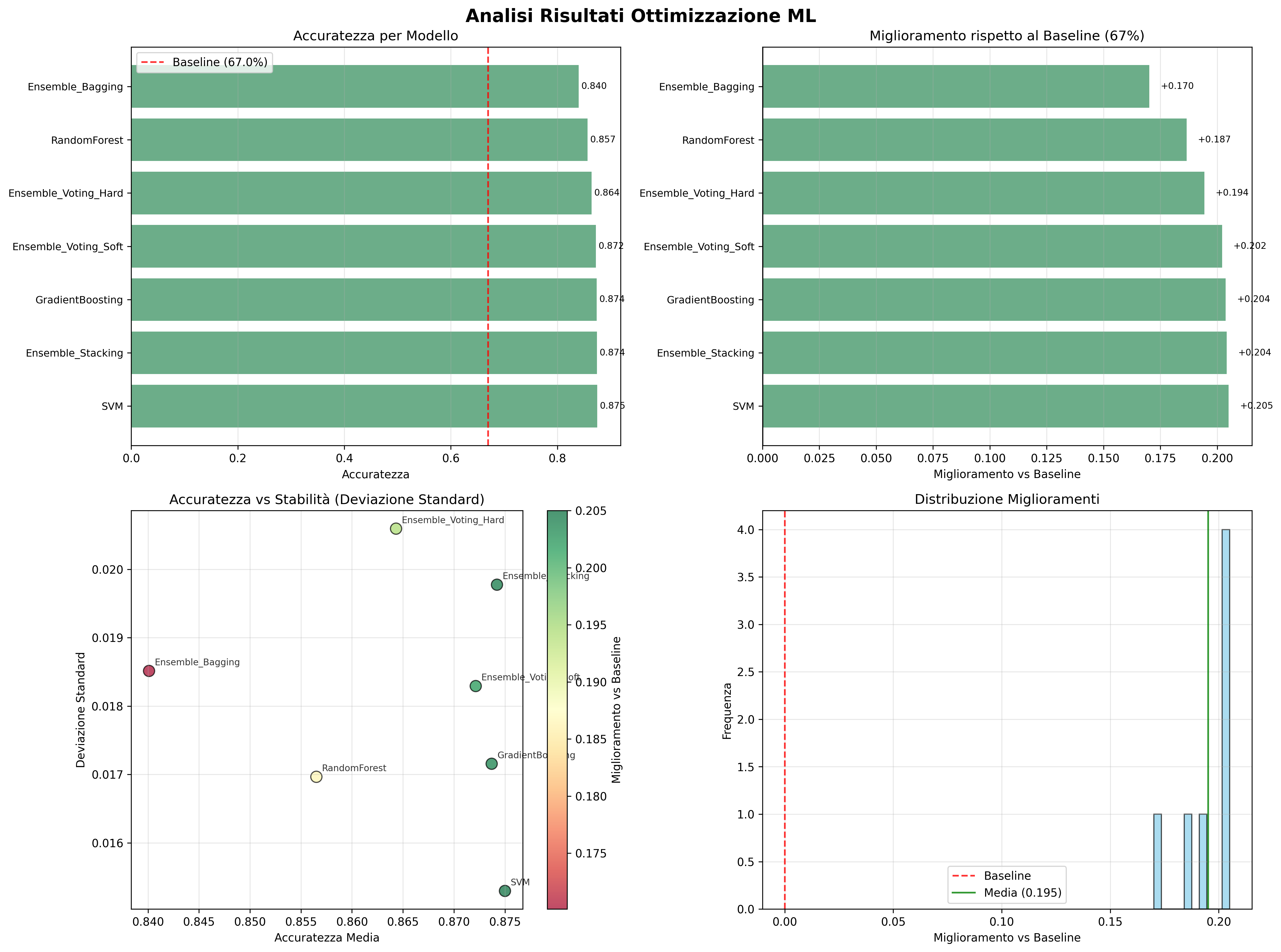


Immagine che contiene testo, diagramma, schermata, linea

Il contenuto generato dall'IA potrebbe non essere corretto.

Immagine che contiene testo, diagramma, schermata, design

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Immagine che contiene testo, schermata, quadrato, diagramma

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Immagine che contiene testo, schermata, Carattere, diagramma

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