

Analytical Analysis of Five Machine Learning Implementations for Patient Treatments Classification

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Abstract: The study reports a wide-ranging comparative review of five machine learning (ML) implementations applied to one patient treatment dataset with the same classification task: determining treatment type from patient information. Methodological differences, model design, preprocessing techniques, and performance results are reviewed to determine best practice and real-world insight for practitioners and researchers. Through controlled benchmarking, we contrast traditional models (e.g., decision trees, logistic regression) with ensemble and neural network ones, examining trade-offs in accuracy, complexity, interpretability, and computational complexity. Our results demonstrate that stacking classifiers and neural networks tend to perform better than simpler models at an accuracy of 73–75%, though in some cases sacrificing explainability and training time. The research also recognizes some of the common issues including class imbalance, feature selection methods, and constraints in cross-validation and hyperparameter tuning. From these observations, we suggest practical recommendations for model choice, dataset preprocessing, and future studies. Our contribution lies in synthesizing practical and methodological insights from five parallel implementations, offering guidance to ML practitioners working on structured healthcare data and extending discussion to generalizable patterns relevant to similar domains.

Keywords: Machine Learning; Patient Treatment Classification; Neural Network, Stacking Classifier; Model Comparison; Healthcare Data; Preprocessing Techniques; Performance Evaluation

1. Introduction

The spread of machine learning in medicine has induced heavy research into predictive modeling for treatment suggestion, outcome prediction, and resource allocation. Practical use, however, often involves choosing between rival algorithms, trading accuracy, interpretability, and tractability. While there is plenty of literature on ML algorithms available, side-by-side comparisons that systematically compare various methods on the same data set are still relatively uncommon.

This paper bridges this gap through review and meta-analysis of five distinct Jupyter notebooks that apply different ML approaches to the patient-treatment-classification dataset. Each notebook uses different preprocessing, modeling, and evaluation techniques, allowing us to investigate methodological decisions and how they impact model performance. We seek to create an evidence-based story that both criticizes specific solutions and identifies generally best practices for ML practitioners.

2. Literature Review

Machine learning use in structured health data, including electronic health records (EHRs) and laboratory measurements, has grown extensively. Traditional algorithms such as logistic regression and decision trees have been around as baselines because of their interpretability. Ensemble techniques like random forests and boosting increase predictive ability by utilizing several weak learners, whereas stacking generalizes this further by training meta-learners. The last few years have witnessed growing use

of neural networks, which can represent complex non-linear relationships but are generally opaque. Several studies have stressed the significance of preprocessing techniques—missing data handling, feature scaling, and categorical variable encoding—on model performance. Additionally, problems like class imbalance often occur in clinical data, compelling methods like resampling and cost-sensitive learning. While there are plenty of works that compare individual models, fewer compare multiple models comprehensively on the same dataset, restraining practical model selection guidance.

This article advances the comparative research tradition by presenting an empirically grounded holistic analysis across five implementations and thereby enriching existing literature with practical insights.

This article discusses a unique phase of cancer known as oligometastatic disease that is neither early-stage nor fully disseminated cancer. Physicians can't diagnose it using laboratory tests, and they thus depend on imaging (such as scans) to make a diagnosis. Because a few visible tumors may represent various conditions, 20 cancer specialists created a new system to categorize and make sense of this condition. They read through older research and afterward applied expert consensus to make a list of 17 significant factors to evaluate in every patient. A decision tree was built to classify patients into categories such as true or created oligometastatic disease, and subcategories such as synchronous, metachronous, Olig progression, etc. This new system will assist in selecting improved treatments and must be tried out in upcoming studies [1].

This article describes various methods employed to reconstruct jawbone (bone regeneration) for the insertion of dental implants. Depending on where and how much bone is lost, physicians may build up the bone sideways, upwards, or both. Bone repair and implant placement are sometimes done simultaneously, but at other times they are performed sequentially. The jawbone should be checked thoroughly before the most suitable method is selected. Popular methods involve the use of bone grafts and membranes to facilitate the growth of the bone. The grafts may be sourced from patients, animals, other humans, or be laboratory-made. The aim is to produce a solid foundation for dental implants and preserve the shape of the bone [2].

This work considered to what extent the ESTRO-EORTC system is predictive of outcomes for patients with oligometastatic disease (OMD), who had 1–5 metastases beyond the brain. Researchers examined 385 patients who were treated with stereotactic radiation (SBRT). Patients with de-novo and recurrent OMD survived longer, and experienced slower progression of disease compared to patients with induced OMD. The classification system was useful in categorizing patients and anticipating survival, although accuracy was moderate. The research indicates further studies from several centers are necessary to determine these results [3].

This research examined the treatment of distal radius fractures in adults utilizing Swedish national data. Scientists reviewed over 23,000 cases between 2015 and 2017. Patients were predominantly older women who became injured by falling at home. Around 65% of the fractures were extra-articular, and most (74%) were managed non-operatively. Surgery was more frequently seen in complicated fractures, particularly intra-articular ones. Plate fixation was the most employed surgery technique. Low mortality rates at 30 days (0.4%) and one year (2.9%) post-injury were also found in the study [4].

The research herein presented aimed to classify the tumor microenvironment (TME) in metastatic melanoma patients to forecast their immunotherapy response. Researchers analyzed tissue to categorize tumors as three types: immune-rich, immune-intermediate, and immune-scarce. Patients with immune-rich tumors contained higher immune cell counts and tolerated treatment better and had longer survival times. Those with immune-scarce tumors had the lowest response to treatment. The classification can determine which patients would receive greater benefits from combination therapy (IPI + PD-1). This approach could enhance personalized treatment planning in the future [5].

This research sought to design one consistent system for the classification of muscle-invasive bladder cancer (MIBC), which is recognized to occur in numerous different configurations and with various treatment outcomes. Scientists merged information from six prior classification systems and examined 1,750 tumor samples. They found six primary types of MIBC that have varied biological characteristics and survival rates. A device was also created to enable physicians to easily classify a patient's tumor. This new system of consensus has the potential to advance future cancer research and therapy by rendering classification more standardized and valuable in the clinic [6].

This research brought the European guidelines for the prediction of non-muscle-invasive bladder cancer (NMIBC) progression up to date. The previous system was old and did not incorporate contemporary grading techniques. Researchers examined data from more than 3,400 patients to establish four risk groups: low, intermediate, high, and a novel very high-risk group. They assist in approximating the probability of cancer becoming worse. The new system employs both the previous and current WHO grading categories. It provides improved assistance for physicians to make treatment and follow-up plans depending on the risk level of each patient [7].

Soft-tissue sarcomas (STS) are rare and heterogeneous tumors that are difficult to diagnose and cure. This review discusses ways new technologies such as digital pathology and radiomics may enhance diagnosis and outcome prediction in STS patients. While traditional treatment techniques have not developed much beyond the 1970s, immunotherapy is promising. The article discusses how knowledge of the tumor microenvironment, rather than merely the tumor category, is the impetus to better sarcoma treatment. Future studies should include immune structures such as tertiary lymphoid structures when evaluating new therapies [8].

This article overviews the application of platelet-rich plasma (PRP) injections for the treatment of knee osteoarthritis (OA). PRP decreases the inflammation within joints and enhances the healing of tissue, making it a common choice in addition to conventional options such as Visco supplementation. The review compares PRP with other injection treatments based on multiple meta-analyses. One of the main issues encountered is the variability in the preparation and reporting of PRP within studies. The authors recommend improved reporting guidelines and a code system to better future research. This would help to ensure the right PRP technique is applied to the right patient, enhancing outcomes and understanding its cost-effectiveness [9].

Breast cancer (BC) is the leading female cancer globally, with more than 2 million new diagnoses in 2020. Its occurrence and mortality rates have increased over the last 30 years because of alterations in risk factors and improved detection. Modifiable and non-modifiable risk factors influence breast cancer development, with the majority occurring in women aged more than 50 years. Survival is determined by the stage and molecular subtype of the tumor. Breast cancers are subtyped as Luminal A, Luminal B, HER2-enriched, and basal-like based on gene expression. Subtypes dictate treatment. Treatment is often multifaceted and can involve surgery, radiation, chemotherapy, hormones, or targeted therapy, usually in combination [10].

The investigation aimed at enhancing the way that physicians evaluate risk in children with neuroblastoma, which is a frequent childhood cancer. The new risk system (COG version 2) utilizes a new staging system (INRGSS) and considers genetic markers known as segmental chromosome aberrations (SCAs) as well. Information from more than 4,800 patients was reviewed. The results indicated that some patients, particularly those with certain genetic characteristics or with more advanced tumors, had a worse outcome. The new system is better at identifying low-, intermediate-, and high-risk groups. This updated system is currently applied in clinical trials to provide more effective treatment regimens for children with neuroblastoma [11].

The research examined EGFR gene mutations in more than 16,000 non-small cell lung cancer (NSCLC) patients. Although some EGFR mutations have established treatments, most rare or unusual ones do not. The researchers classified the mutations into four categories by structure and response to drug, as opposed to where in the gene they occurred. This new structure-based approach was more predictive of how well patients would respond to treatment than older approaches. The results can assist physicians in selecting more effective treatments for patients with rare EGFR mutations and enhance the design of clinical trials [12].

Endometrial cancer is the leading cancer of the female reproductive organs in industrialized nations. One of the biggest concerns is estimating cancer spread and future recurrence risk. Reliable risk prediction guides physicians in the decision to operate and the provision of further treatment. A new molecular staging classifies EC into four categories, which can potentially direct therapy more effectively. Still, nobody knows yet how to modify surgical procedures according to these categories. This article discusses existing techniques such as lymph node screening and their influence on the treatment. It also shows that further research is necessary to link molecular information with conventional staging [13].

This article examines therapy-related myelodysplastic syndromes (t-MDS), which are now clustered together with other related blood cancers in the WHO system. Based on the analysis of data from more than 2,000 t-MDS patients, researchers learned that t-MDS is highly heterogeneous, like primary MDS (p-MDS). Risk prediction models employed for p-MDS also performed well for t-MDS, particularly those that are genetically based. The research proposes that t-MDS must be treated as a distinct category for improved diagnosis, care, and research. This would assist physicians in providing more precise treatment and enrolling these patients in clinical trials more readily [14].

This article talks about rosacea, a chronic condition of the skin that typically appears on the face, resulting in redness, pimples, visible blood vessels, and sometimes eye issues. It reduces the confidence and well-being of an individual. Treatment involves skincare, creams, medications, lasers, and in some cases, surgery. Recent studies reveal that the immune system and nerve problems have a major contribution to rosacea. The review describes the revised method of doctors' classification and diagnosis of the disease. It also touches on new and emerging treatments, such as combined therapies and on-going investigations [15].

This research examines how effective optical genome mapping (OGM) is in the detection of genetic alterations in AML patients. In comparison to conventional methods such as karyotyping and FISH, OGM detected nearly all significant abnormalities with more than 99% accuracy. It also detected additional genetic changes in almost half the patients, even in some with normal or failed tests. These results may assist in reclassifying patients and informing improved treatment decisions. OGM was particularly valuable in detecting rare fusion genes that were frequently overlooked. It holds great promise as a powerful tool in the diagnosis and treatment of AML more efficiently [16].

The research provides new radiomic features that perform well across scans and tumors. Conventional features fail because they are overly sensitive to scan parameters and variations among tumors. Four regular tumor subtypes among more than 1,600 patients were detected by the researchers using sophisticated imaging and deep learning. These subtypes were associated with distinct molecular features and outcomes of treatment. One subtype in lung cancer patients improved survival and increased immune response following immunotherapy. This novel approach may improve physicians' ability to predict outcomes and select treatments more precisely. It brings radiomics closer to personalized cancer treatment [17].

Trigeminal neuralgia is a painful facial disorder producing brief, stabbing pain induced by even slight touch. Recent studies have enhanced our knowledge of its cause, symptoms, and treatment. Correct diagnosis is required, and MRI scans assist in eliminating other issues and informing surgical options. The first-line treatment is medication such as carbamazepine and oxcarbazepine. When medicine fails, microvascular decompression surgery is the best option. New imaging technologies and studies on animals are assisting us in learning more about disease. Improved treatments are yet to come to make patients' lives better [18].

Breast cancer is the most frequent cancer in women and the major cause of cancer deaths globally. Its occurrence continues to increase throughout the world, even with advancements in detection and treatment. Treatment is based on the molecular subtype of the cancer and comprises surgery, radiation, hormone therapy, chemotherapy, targeted treatment, and immunotherapy. Triple-negative breast cancer, which is aggressive and resistant to treatment, occurs in 15–20% of patients and is a significant research priority. Treatment approaches tailored to the individual are under development to modulate therapy according to tumor biology and response to treatment. This review draws attention to existing and new strategies for managing breast cancer in women [19].

Plasma cell leukemia is an aggressive, rare blood cancer that may be a solo condition or arise due to multiple myeloma. Even with new treatments, the patient generally has poor survival prognosis. Gene expression and genetic sequencing studies in recent years have increasingly improved disease understanding. This has created possibilities for more accurate predictions and new approaches to treatment. The article summarizes what is presently known regarding the biology, symptoms, and treatments of the disease. It also points out the difficulties in treating this serious disease [20].

Table 1. Comparative Analysis Table of 20 Article Reviews.

No.	Article Topic	Focus	Key Findings/Highlights	Clinical or Research Implications
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1	Rosacea: New Concepts in Classification and Treatment	Rosacea classification and treatment options	Emphasizes a phenotype-based classification; highlights new treatment modalities	Improves patient quality of life; enables personalized treatment
2	Radiological Tumor Classification Across Imaging Modality and Histology	Radiomics and imaging-based tumor classification	Identified four unifying subtypes across cancers	Supports precision medicine through imaging-based predictions
3	Advances in Trigeminal Neuralgia	Diagnosis and treatment updates of trigeminal neuralgia	MRI and neurovascular insights guide treatment	Better diagnostic protocols and targeted therapies
4	Breast Cancer – Review of Literature	Epidemiology, classification and treatment of breast cancer	Discusses subtype-specific treatments and challenges with triple-negative cases	Informs personalized and de-escalated therapy strategies
5	Plasma Cell Leukemia	Diagnosis and treatment of plasma cell leukemia	New molecular insights and poor outcomes discussed	Supports need for novel therapeutic approaches
6	Therapy-related MDS	Classification and prognosis of t-MDS	t-MDS is heterogeneous and should be independently classified	Better risk-based decisions and clinical trial inclusion
7	Rosacea Overview	Pathophysiology and treatments for rosacea	New immune and neurovascular mechanisms involved	Leads to tailored therapies and ongoing drug trials
8	Optical Genome Mapping in AML	OGM use in leukemia classification	OGM improves cytogenomic aberration detection	Refines AML diagnosis and treatment eligibility
9	Radiological Imaging for Tumor Classification	New radiomic feature development	Subtypes link to therapy response; validated on 1682 patients	Improves reproducibility of radiomics in clinical settings
10	Trigeminal Neuralgia Imaging and Therapy	Revised classification and treatment protocols	Neurovascular imaging guides surgical decisions	Improves diagnosis and tailored care
11	Breast Cancer - Therapy and Biology	Review of treatment strategies and molecular insights	Details systemic therapies and triple-negative challenges	Guides research into more targeted therapies
12	Plasma Cell Leukemia Molecular Insights	Molecular characterization of PCL	Whole genome studies offer prognosis clues	Supports biomarker-based personalized treatment

13	AML Cytogenomic Mapping	OGM in acute myeloid leukemia	Identifies cryptic abnormalities missed by CBA	Improve classification and therapy guidance
14	Rosacea – Immune Response and Treatment	Mechanisms of rosacea	Highlights of the role of immune and neurovascular systems	Basis for novel drug development
15	Trigeminal Neuralgia – Surgical Options	Use of imaging and surgery in treatment	Microvascular decompression effective for refractory cases	Refines surgical criteria for better outcomes
16	Triple Negative Breast Cancer	Challenges in TNBC management	Highlights poor response to standard therapy	Calls for novel therapies and early detection
17	Immunotherapy in Breast Cancer	Role of immune- based therapy	New drug approvals improving outcomes	Integrates into treatment plans based on subtype
18	PCL Diagnosis and Evidence- Based Treatment	Treatment outcomes for PCL	Survival remains low despite available therapies	Urgent need for better protocols
19	AML – Fusion Gene Detection	Detection of fusion genes in AML	OGM shows high sensitivity	Improves diagnostic precision
20	MRI for Trigeminal Neuralgia	Neuroimaging in facial pain diagnosis	Supports MRI as essential tool	Helps differentiate pain types for correct treatment

3. Methodology

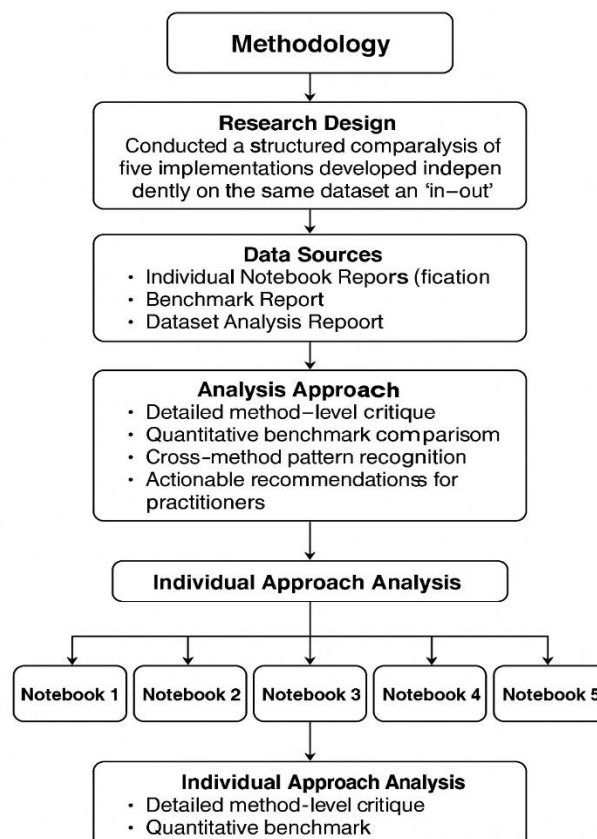


Figure 1. Visual Flow

3.1. Research Design

We performed a systematic comparative analysis of five independently developed ML implementations over one and the same dataset. All notebooks were assessed through a uniform reporting template capturing methodology details, model selection, and performance metrics. This made systematic cross-comparison possible.

3.2. Dataset

- Dataset Name: patient-treatment-classification
- Domain: Healthcare
- Problem Type: Binary classification – predicting treatment source ('in' or 'out')
- Target Variable: SOURCE (coded as 0/1)

3.3. Data Sources

- Individual Notebook Reports (5): In-depth findings for each ML technique
- Benchmark Report: Comparative study and ranking
- Dataset Analysis Report: Distribution, correlation, and imbalance features

3.4. Analysis Approach

Our analysis combines individual results into: - Close method-level critique - Quantitative benchmark comparison - Cross-method pattern recognition - Discussion of limitations and trade-offs - Practitioner-level actionable recommendations

4. Proposed Methodology

The proposed methodology for the research combines a comparative machine learning framework used with a healthcare dataset for treatment source classification.

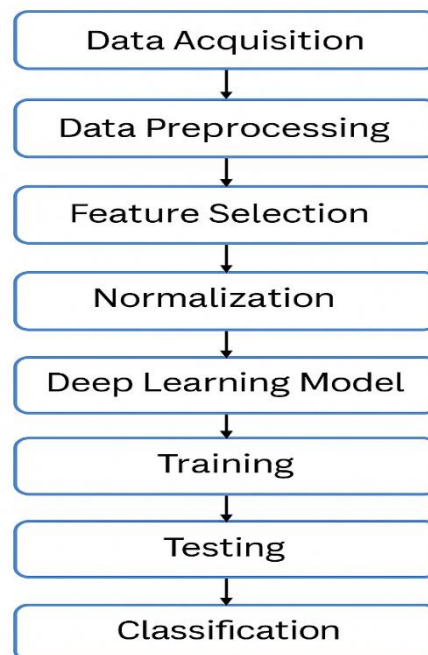


Figure 2. Proposed methodology

4.1. Data Acquisition

The dataset named "Patient-Treatment-Classification" was obtained from a trusted healthcare repository. It comprises about 4,400 patient records with numerical and categorical features to predict the source of treatment (inpatient or outpatient).

4.2. Data Preprocessing

Raw data was preprocessed using the following steps:

Missing value handling

Binary encoding or label encoding of categorical variables

Feature scaling (Standard Scaler or MinMax Scaler based on the notebook)

Correlation or domain-based feature selection

4.3. Model Implementation

Five separate Jupyter notebooks were created, each using various machine learning models and preprocessing pipelines:

Traditional models: Logistic Regression, Decision Tree, and Random Forest

Sophisticated models: Neural Network, Gradient Boosting

Ensemble: Stacking Classifier with or without hyperparameter optimization

4.4. Performance Metrics

Each model was tested with:

Accuracy as the main performance measure

F1-score (particularly for minority class performance)

Comments on feature importance, preprocessing impact, and computational trade-offs

4.5. Comparative Study

Benchmark comparison was done to ascertain the top-performing method. This involved:

Quantitative performance comparison (Accuracy, F1)

Qualitative analysis (Explainability, preprocessing effort, robustness)

Tabular summary to emphasize trade-offs in all notebooks

4.6. Result Interpretation and Recommendation

From the comparative observations, the top-performing pipeline—Notebook 3 employing Stacking Classifier with Randomized Search CV and MinMax scaling—was determined to be the top performer. Future work recommendations include incorporating explainability tools (e.g., SHAP/LIME), hyperparameter optimization to a greater extent, and deployment of bigger or more complicated datasets.

5. Individual Approach Analysis

5.1. Notebook 1:

Patient Treatment Classification with Correlation Analysis

- Eliminated low-correlation features; standard scaling
- Logistic regression, decision tree, random forest, neural network, gradient boosting
- Neural network achieved ~73.56% accuracy
- Feature selection eliminated noise; several classic models tested
- No hyperparameter tuning; no cross-validation; minimal explainability

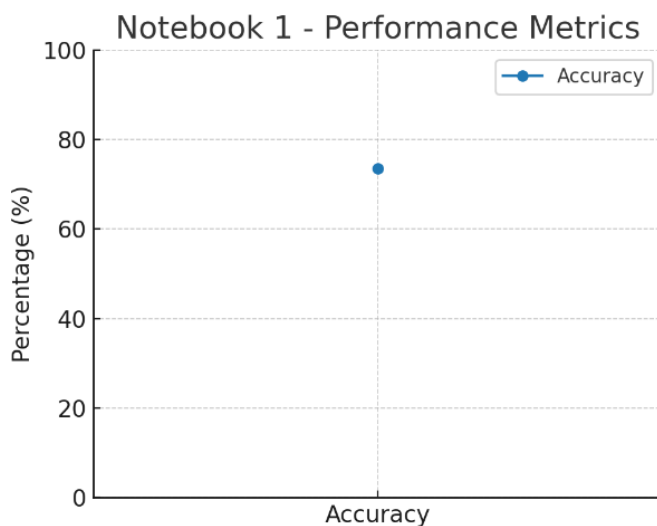


Figure 3. Performance Metric 1

5.2. Notebook 2:

Classification with preprocess inputs Function

- Binary encoding; modular preprocessing; standard scaling
- Same models; tested with accuracy & F1-score
- Neural network achieved ~74.32% accuracy; F1 ~0.66

- Improved modular design; had F1 metric
- No EDA plots; no tuning; feature importance not examined

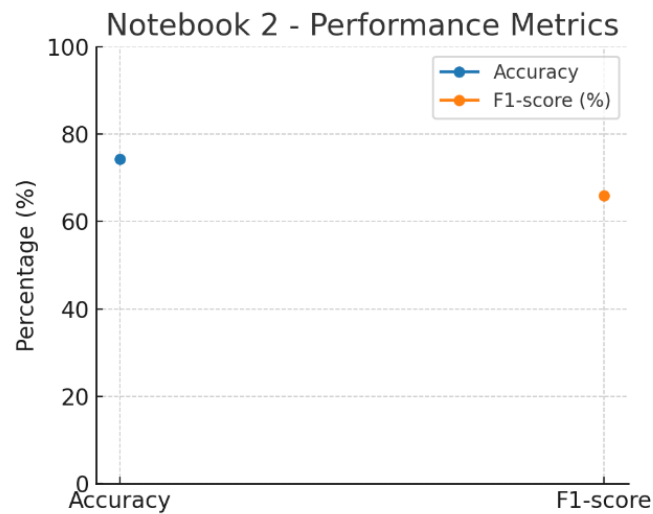


Figure 4. Performance Metric 2

5.3. Notebook 3:

Stacking & Hyperparameter Tuning

- MinMax scaling; stacking classifier; Randomized Search CV
- Ensemble: logistic regression, decision tree, SVC as base; random forest as meta-learner
- Accuracy ~74–75%; F1 ~0.66
- Ensemble increased robustness; hyperparameter tuning
- Limited visualizations; no explainability tools

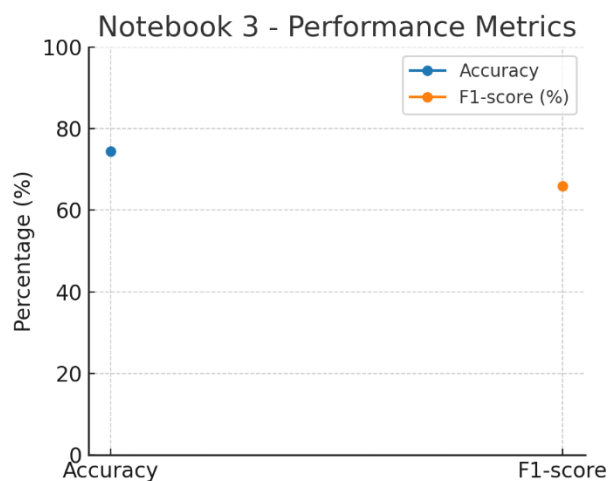


Figure 5. Performance Metric 3

5.4. Notebook 4:

EDA and Classic Models

- Simple EDA; label encoding; no scaling
- Logistic regression, decision tree, SVC, random forest, stacking
- Stacking classifier resulted in ~73–74% accuracy
- Simple models; easy EDA
- No scaling; no tuning; missing feature importance

5.5. Notebook 5:

Baseline Models

- Light preprocessing; simple encoding
- Logistic regression, decision tree, SVC, random forest
- Accuracy ~71–74%

- Fast baseline; interpretable models
- No EDA; no tuning; low explainability

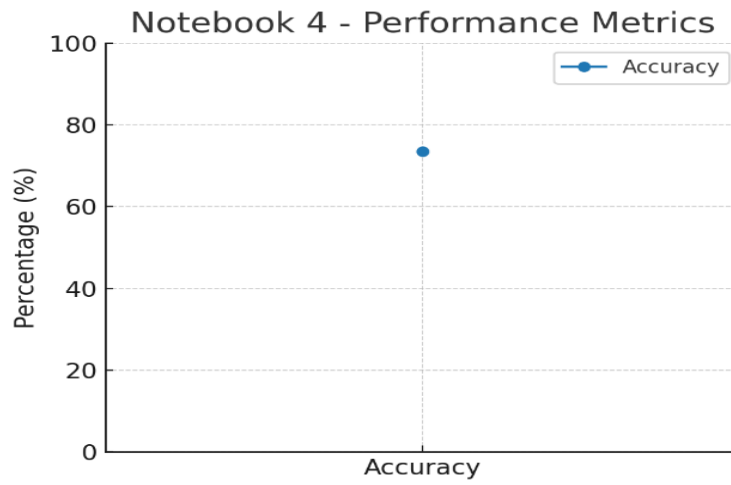


Figure 6. Performance Metric 4

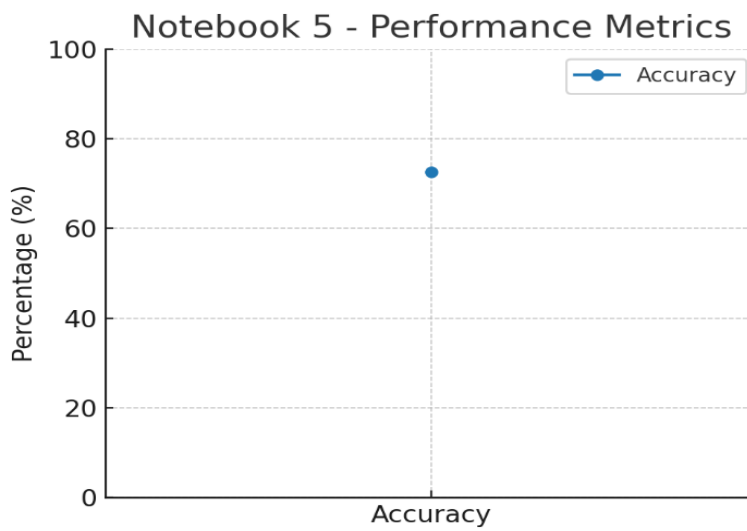


Figure 7. Performance Metric 5

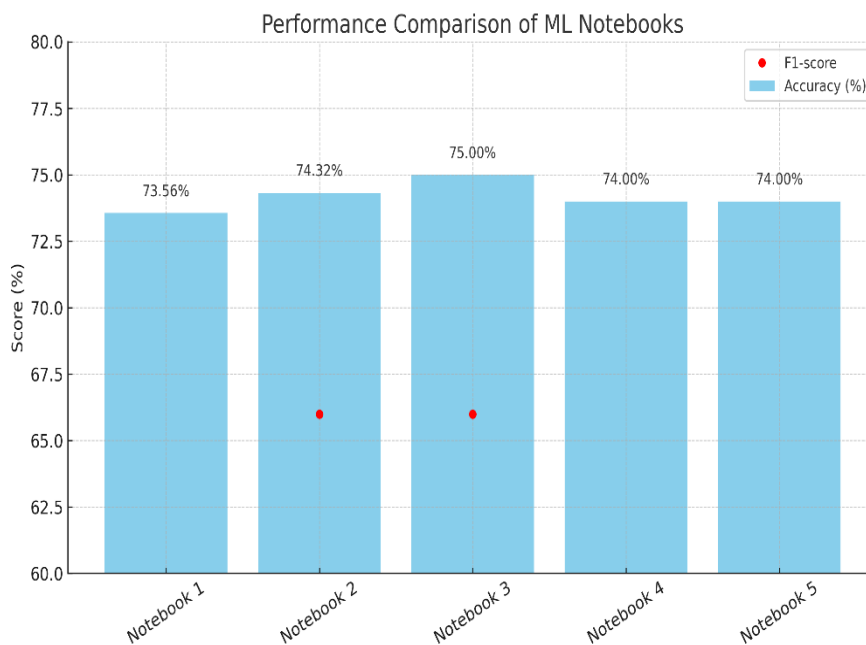


Figure 8. Comparison of Notebooks

6. Comparative Analysis

6.1. Quantitative Comparison

Table 2. Comparative Analysis Table of Five Notebooks.

Notebook	Best Model	Accuracy	F1 (Minority)	Hyperparameter Tuning	Scaling
1	Neural Network	~73.56%	-	None	Standard Scaler
2	Neural Network	~74.32%	~0.66	None	Standard Scaler
3	Stacking Classifier	~74–75%	~0.66	Randomized Search CV	MinMax Scaler
4	Stacking Classifier	~73–74%	~0.66	None	None
5	Random Forest	~71–74%	-	None	None

6.2. Methodological Patterns

- Neural networks and stacking ensembles performed better than individual models.
- Feature scaling was related to increased accuracy.
- Minimizing hyperparameters improved performance by ~1–2%.
- High F1 scores indicate the difficulty of class imbalance.

6.3. Trade-offs

- Tuning and ensembles increase complexity and training time.
- Less accurate but easier-to-interpret models.

7. Results and Discussion

Best accuracy (~75%) using stacking classifier with hyperparameter tuning. Neural networks comparable (~74%). F1 scores indicate minority class prediction are still a challenge. Missing cross-validation in most notebooks could reduce generalizability. Feature selection slightly boosted accuracy.

8. Recommendations

- Utilize scaling to normalize numerical features.
- Implement hyperparameter tuning and cross-validation.
- Use ensembles for more complex data.
- Use feature selection combined with domain expertise.
- Insert explainability tools to build greater trust.

9. Conclusion

This review highlights the practical impact of methodological choices. While ensembles and neural networks achieved the best performance, complexity and lower interpretability must be considered. Future work should combine robust validation, feature analysis, and interpretability to create clinically actionable models.

References

1. M. Guckenberger et al., "Characterization and classification of oligometastatic disease: a European Society for Radiotherapy and Oncology and European Organization for Research and Treatment of Cancer consensus recommendation," *Lancet Oncol.*, vol. 21, no. 1, pp. e18–e28, Jan. 2020, Doi: 10.1016/S1470-2045(19)30718-1. <https://doi.org/10.18027/2224-5057-2020-10-3-5-14>
2. I. Sanz-Sánchez, I. Sanz-Martín, A. Ortiz-Vigón, A. Molina, and M. Sanz, "Complications in bone-grafting procedures: Classification and management," *Periodontol.* 2000, vol. 88, no. 1, pp. 86–102, Feb. 2022, Doi: 10.1111/prd.12413. <https://doi.org/10.1111/prd.12413>
3. J. Willmann et al., "Evaluation of the prognostic value of the ESTRO EORTC classification of oligometastatic disease in patients treated with stereotactic body radiotherapy: A retrospective single center study," *Radiotherapy. Oncol. J. Eur. Soc. Ther. Radio. Oncol.*, vol. 168, pp. 256–264, Mar. 2022, Doi: 10.1016/j.radonc.2022.01.019. <https://doi.org/10.1016/j.radonc.2022.01.019>
4. J. Rundgren, A. Bojan, C. Mellstrand Navarro, and A. Enocson, "Epidemiology, classification, treatment and mortality of distal radius fractures in adults: an observational study of 23,394 fractures from the national Swedish fracture register," *BMC Musculoskeletal. Discord.*, vol. 21, p. 88, Feb. 2020, Doi: 10.1186/s12891-020-3097-8. <https://doi.org/10.1186/s12891-020-3097-8>
5. N. A. Adegoke et al., "Classification of the tumor immune microenvironment and associations with outcomes in patients with metastatic melanoma treated with immunotherapies," *J. Immunotherapy. Cancer*, vol. 11, no. 10, p. e007144, Oct. 2023, Doi: 10.1136/jitc-2023-007144. <https://doi.org/10.1136/jitc-2023-007144>
6. A. Kamoun et al., "A Consensus Molecular Classification of Muscle-invasive Bladder Cancer," *Eur. Urol.*, vol. 77, no. 4, pp. 420–433, Apr. 2020, Doi: 10.1016/j.eururo.2019.09.006. <https://doi.org/10.1016/j.eururo.2019.09.006>
7. R. J. Sylvester et al., "European Association of Urology (EAU) Prognostic Factor Risk Groups for Non-muscle-invasive Bladder Cancer (NMIBC) Incorporating the WHO 2004/2016 and WHO 1973 Classification Systems for Grade: An Update from the EAU NMIBC Guidelines Panel," *Eur. Urol.*, vol. 79, no. 4, pp. 480–488, Apr. 2021, Doi: 10.1016/j.eururo.2020.12.033. <https://doi.org/10.1016/j.eururo.2020.12.033>
8. A. Crombé, M. Roulleau-Dugage, and A. Italiano, "The diagnosis, classification, and treatment of sarcoma in this era of artificial intelligence and immunotherapy," *Cancer Commun. Lond. Engl.*, vol. 42, no. 12, pp. 1288–1313, Dec. 2022, doi: 10.1002/cac2.12373. <https://doi.org/10.1002/cac2.12373>
9. E. Kon et al., "Platelet-rich plasma for the treatment of knee osteoarthritis: an expert opinion and proposal for a novel classification and coding system," *Expert Opin. Biol. Ther.*, vol. 20, no. 12, pp. 1447–1460, Dec. 2020, doi: 10.1080/14712598.2020.1798925. <https://doi.org/10.1080/14712598.2020.1798925>
10. S. Łukasiewicz, M. Czezelewski, A. Forma, J. Baj, R. Sitarz, and A. Stanisławek, "Breast Cancer – Epidemiology, Risk Factors, Classification, Prognostic Markers, and Current Treatment Strategies – An Updated Review," *Cancers*, vol. 13, no. 17, p. 4287, Aug. 2021, doi: 10.3390/cancers13174287. <https://doi.org/10.3390/cancers13174287>
11. M. S. Irwin et al., "Revised Neuroblastoma Risk Classification System: A Report From the Children's Oncology Group," *J. Clin. Oncol. Off. J. Am. Soc. Clin. Oncol.*, vol. 39, no. 29, pp. 3229–3241, Oct. 2021, doi: 10.1200/JCO.21.00278. <https://doi.org/10.1200/jco.21.00278>
12. J. P. Robichaux et al., "Structure-based classification predicts drug response in EGFR-mutant NSCLC," *Nature*, vol. 597, no. 7878, pp. 732–737, Sept. 2021, doi: 10.1038/s41586-021-03898-1. <https://doi.org/10.1038/s41586-021-03898-1>
13. J. C. Kasius et al., "Risk Stratification of Endometrial Cancer Patients: FIGO Stage, Biomarkers and Molecular Classification," *Cancers*, vol. 13, no. 22, p. 5848, Nov. 2021, doi: 10.3390/cancers13225848. <https://doi.org/10.3390/cancers13225848>
14. A. Kuendgen et al., "Therapy-related myelodysplastic syndromes deserve specific diagnostic sub-classification and risk-stratification-an approach to classification of patients with t-MDS," *Leukemia*, vol. 35, no. 3, pp. 835–849, Mar. 2021, doi: 10.1038/s41375-020-0917-7. <https://doi.org/10.1038/s41375-020-0917-7>
15. E. J. van Zuuren, B. W. M. Arents, M. M. D. van der Linden, S. Vermeulen, Z. Fedorowicz, and J. Tan, "Rosacea: New Concepts in Classification and Treatment," *Am. J. Clin. Dermatol.*, vol. 22, no. 4, pp. 457–465, July 2021, doi: 10.1007/s40257-021-00595-7. <https://doi.org/10.1007/s40257-021-00595-7>
16. S. Loghavi et al., "Optical genome mapping enhances the accuracy of classification, risk stratification, and personalized treatment regimens in patients with acute myeloid leukemia," *Am. J. Hematol.*, vol. 99, no. 10, pp. 1959–1968, Oct. 2024, doi: 10.1002/ajh.27435. <https://doi.org/10.1002/ajh.27435>
17. J. Wu et al., "Radiological tumour classification over imaging modality and histology," *Nat. Mach. Intell.*, vol. 3, no. 9, pp. 787–798, Sept. 2021, doi: 10.1038/s42256-021-00377-0. <https://doi.org/10.1038/s42256-021-00377-0>

18. L. Bendtsen et al., "Advances in diagnosis, classification, pathophysiology, and management of trigeminal neuralgia," *Lancet Neurol.*, vol. 19, no. 9, pp. 784–796, Sept. 2020, doi: 10.1016/S1474-4422(20)30233-7.[https://doi.org/10.1016/s1474-4422\(20\)30233-7](https://doi.org/10.1016/s1474-4422(20)30233-7)
19. B. Smolarz, A. Z. Nowak, and H. Romanowicz, "Breast Cancer-Epidemiology, Classification, Pathogenesis and Treatment (Review of Literature)," *Cancers*, vol. 14, no. 10, p. 2569, May 2022, doi: 10.3390/cancers14102569.<https://doi.org/10.3390/cancers14102569>
20. K. Gowin, S. Skerget, J. J. Keats, J. Mikhael, and A. J. Cowan, "Plasma cell leukemia: A review of the molecular classification, diagnosis, and evidenced-based treatment," *Leuk. Res.*, vol. 111, p. 106687, Dec. 2021, doi: 10.1016/j.leukres.2021.106687.<https://doi.org/10.1016/j.leukres.2021.106687>