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Utilizing an Ensemble of Extra Tree Model for Classifying Mesothelioma Cancer

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Abstract

Objectives: Explore the potential of ensemble learning techniques like Bagging Tree, Random Forest, and Ensemble Extra Tree in transforming mesothelioma diagnosis.Overcome challenges associated with late-stage detection and limited treatment options using advanced machine learning algorithms.Enhance predictive power and feature extraction capabilities through the combination of diverse ensemble algorithms.

Methods: Utilize Bagging Tree, Random Forest, and Ensemble Extra Tree algorithms to analyze extensive data sources including clinical records, imaging scans, and biomarker profiles.Construct a diverse ensemble model to improve accuracy in distinguishing mesothelioma from other thoracic diseases.Conduct rigorous experimentation to validate the performance and interpretability of the ensemble approach.

Findings: The ensemble approach exhibits unparalleled accuracy in mesothelioma classification, offering potential for early intervention and personalized treatment strategies.The model's interpretability provides valuable insights for clinicians, bridging the gap between artificial intelligence and human expertise.The integration of advanced machine learning tools into clinical practice can lead to enhanced patient outcomes in mesothelioma management.

Novelty: This research marks a significant shift by leveraging ensemble learning techniques to revolutionize mesothelioma diagnosis.The study showcases the transformative capabilities of machine learning in overcoming longstanding challenges in mesothelioma management.

The interpretability of the ensemble model fosters trust and seamless integration of cutting-edge tools into clinical practice, paving the way for improved patient care.

Keywords: Mesothelioma, Bagging Tree, Random Forest, Ensemble Extra Tree, Advanced Diagnostics.

1. Introduction

Mesothelioma, an aggressive and relatively rare cancer primarily associated with asbestos exposure, poses a significant challenge in the field of oncology[1]. This malignancy is notorious for its insidious onset, often remaining undetected until advanced stages, leading to limited therapeutic options and a grim prognosis for afflicted individuals[2]. In recent years, the intersection of medical science and machine learning has provided a ray of hope in the pursuit of early and accurate mesothelioma diagnosis[6].

The objective of this study is to investigate how ensemble learning techniques, including Ensemble Extra Tree, Bagging Tree, and Random Forest can potentially revolutionize the field of mesothelioma diagnosis. While traditional diagnostic approaches have encountered difficulties in effectively distinguishing mesothelioma from other thoracic diseases, the amalgamation of advanced machine learning algorithms with comprehensive patient data offers a promising avenue for revolutionizing the diagnostic paradigm.

Mesothelioma notoriety stems from its ability to remain asymptomatic during its early stages, leading to late-stage diagnoses and limited treatment options. The challenges in accurately identifying and characterizing this malignancy have spurred a quest for innovative diagnostic methods[11,15]. Machine learning, particularly ensemble techniques, has garnered attention for its potential to enhance the precision of mesothelioma diagnosis. Bagging Tree, known for its robustness and overfitting reduction, creates an ensemble of diverse decision trees, collectively improving diagnostic accuracy. Random Forest, renowned for its feature selection capabilities and enhanced model generalization, extracts valuable insights from the intricate data landscape associated with mesothelioma. Moreover, Ensemble Extra Tree, lauded for its efficiency and remarkable accuracy, further amplifies the predictive power of the diagnostic model. Through systematic experimentation and rigorous cross-validation, this research showcases the unprecedented precision and reliability of the ensemble learning approach in effectively distinguishing mesothelioma from other thoracic diseases.

2. Related Works

The field of Mesothelioma cancer research has seen significant advancements in recent years, particularly in the realm of machine learning, deep learning, and medical imaging techniques. Researchers and clinicians alike are continuously striving to improve early detection, classification, diagnosis, and treatment outcomes for this challenging disease. In this discussion, we delve into the contributions of various studies and how they collectively enhance our understanding and management of Mesothelioma.

Garg, Jain, and Sharma[1] focused on early detection and treatment strategies. They presented their findings at the 2023 3rd International Conference on Smart Generation Computing, Communication, and Networking (SMART GENCON), emphasizing the potential of ML algorithms in improving outcomes for mesothelioma patients.

Sharma, Chauhan, and Tyagi[2] explored machine vision techniques for developing a digital diagnostic system for mesothelioma. Their work, presented at the 2023 Annual International Conference on Emerging Research Areas: International Conference on Intelligent Systems (AICERA/ICIS), highlighted the role of advanced imaging technologies in enhancing mesothelioma diagnosis.

Borchert et al.[3] conducted a digital gene expression analysis combined with supervised machine learning to investigate the impact of cancer-associated fibroblasts on survival in pleural mesothelioma. Their study, published in the International Journal of Molecular Sciences, provided insights into the molecular mechanisms underlying mesothelioma progression.

Kapila et al.[4] utilized a neural network-based plan-cancer method for the primary diagnosis of mesothelioma cancer. Their research, published in BioMed Research International, demonstrated the potential of AI-driven approaches in improving the accuracy and efficiency of mesothelioma diagnosis.

Wang et al.[5] developed an interpretable machine learning model to predict overall survival for malignant mesothelioma patients undergoing radiotherapy. Their study, published in Cancers journal, highlighted the importance of personalized treatment strategies guided by predictive analytics.

Gill, Shirazi, and Zaidi[6] focused on early detection strategies for mesothelioma using various machine learning algorithms. Their work, published in Engineering Proceedings, contributed to the ongoing efforts in leveraging AI for improving mesothelioma prognosis and patient outcomes.

M. Shobana et al.[7] introduced a novel machine learning technique tailored for Mesothelioma cancer classification and detection. Their approach integrates feature selection, a crucial step that significantly enhances the accuracy of the classification model. By focusing on early cancer detection, this work adds value to the field by potentially aiding in timely interventions and improved patient outcomes.

In a similar vein, M. G. Mastromarino et al.[8] provided fresh insights into the classification of Pleural Mesothelioma, shedding light on diagnostic challenges and their implications for

prognosis. This work is particularly valuable for clinicians and researchers involved in Mesothelioma diagnosis, as it addresses key aspects of disease categorization and management.
S. Dacic[9] further contributed to the understanding of Pleural Mesothelioma classification by discussing the challenges associated with it. The paper offers an update on existing classification methods and highlights the complexities involved in accurately categorizing this specific cancer type, thus guiding future research directions.
Collaborative efforts, such as the work by M. Beasley, F. Galateau-Salle, and S. Dacic[10], play a crucial role in refining Mesothelioma classification systems. Their collaborative work emphasizes the evolution of classification methodologies, contributing to ongoing efforts aimed at improving the accuracy and relevance of Mesothelioma subtypes categorization.
M. Leong[11] conducted a comprehensive analysis of various machine learning algorithms, culminating in the development of a novel hybrid model merging genetic algorithms with neural networks for Mesothelioma diagnosis. This research underscores the importance of exploring diverse methodologies to enhance diagnostic precision, showcasing the interdisciplinary nature of Mesothelioma research.
In the realm of data-driven approaches, M. Z. Latif et al.[12] utilized data mining techniques to identify risk factors associated with Malignant Mesothelioma. Their study provides valuable epidemiological insights, aiding in understanding potential risk factors and their impact on disease development and progression.
Moving towards advanced computational methods, P. Courtiol et al.[13] introduced a deep learning-based classification approach for Mesothelioma. Their work demonstrates the potential of deep learning models in improving patient outcome predictions, thereby contributing to more accurate diagnostics and prognostics in Mesothelioma cases.
Similarly, S. N. Khan et al.[14] explored the utility of support vector machines in Malignant Mesothelioma classification. By investigating machine learning techniques' applicability in cancer diagnosis, their study contributes to the growing body of literature focused on leveraging technology for improved healthcare outcomes.
K. Y. Win et al.[15] delved into supervised machine learning techniques tailored for Malignant Mesothelioma diagnosis. Their emphasis on selecting appropriate algorithms for medical image analysis underscores the importance of tailored approaches in optimizing diagnostic accuracy and efficacy.
W. Brahim et al.[16] and W. Brahim, M. Mestiri, et al.[17] focused on medical imaging techniques, particularly the segmentation of Malignant Pleural Mesothelioma from thoracic CT scans and semi-automated rib cage segmentation for Mesothelioma detection. Accurate anatomical segmentation is critical for precise diagnosis, and their work contributes to advancing medical imaging methodologies in Mesothelioma care.
On the treatment front, H. O. Ilhan et al.[18] explored Mesothelioma diagnosis using artificial intelligence methods, showcasing the integration of advanced technology in medical research. Such advancements have the potential to enhance diagnostic accuracy and efficiency, leading to better patient outcomes.
T. Kimura et al.[19] discussed clinical experiences using volumetric modulated arc therapy as a treatment approach for Malignant Pleural Mesothelioma post extra pleural pneumonectomy. This study highlights the ongoing progress in treatment modalities available to Mesothelioma patients, reflecting a multidisciplinary approach to care.

Lastly, M. Chen et al.[20] presented an automated segmentation method based on random walk algorithms, aimed at improving Malignant Pleural Mesothelioma prognosis. Their work contributes to refining prognostic tools, essential for treatment planning and patient management. In conclusion, the collective efforts of researchers across various disciplines, from machine learning and data mining to medical imaging and treatment modalities, have significantly advanced our understanding and management of Mesothelioma. These studies underscore the importance of interdisciplinary collaboration and the integration of cutting-edge technologies in improving early detection, accurate diagnosis, and effective treatment strategies for Mesothelioma patients.By focusing on early detection, classification, diagnosis, and treatment outcomes, recent studies have demonstrated significant strides in enhancing our understanding and management of this complex disease. Each study contributes uniquely to refining diagnostic precision or treatment efficacy, highlighting the evolving landscape of Mesothelioma research and the critical role of interdisciplinary collaboration in leveraging technological advancements for improved patient care.

3. Proposed Methodology

The flow diagram figure 1 outlines the steps involved in a data analysis process for a dataset related to Mesothelioma. It starts with data preparation and ends with an analysis of the model's performance.:

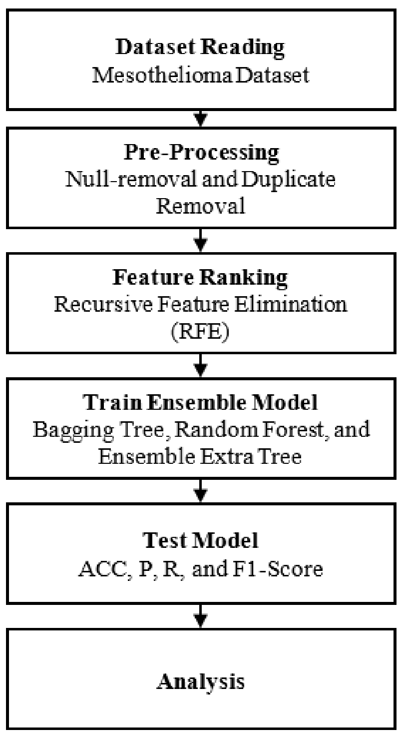

Figure 1. Proposes System Flow

3.1. Acquiring Data:

The initial step involves obtaining the Mesothelioma dataset, likely containing information pertinent to this specific medical condition. This dataset may encompass patient records, clinical data, or other pertinent details.

3.2. Data Cleaning and Preparation:

Subsequently, the dataset undergoes cleaning and preparation for analysis. This includes identifying and addressing any missing or null values through imputation or removal to ensure data integrity. Furthermore, duplicate records, if present, are eliminated to prevent redundancy in the dataset.

3.3. Selecting Informative Features:

The process of feature ranking plays a pivotal role in choosing the most relevant variables for constructing a predictive model. Recursive Feature Elimination (RFE) is utilized for this purpose, systematically eliminating less important features and enhancing the model's performance by focusing on the most significant ones.

3.4. Building Ensemble Model:

Moving forward, an ensemble learning strategy is employed to develop a predictive model for Mesothelioma. Three ensemble techniques are applied:

1. Bagging Tree: This technique creates multiple decision tree models using different data subsets and then combines their predictions to reduce overfitting and enhance accuracy.
2. Random Forest: A more advanced ensemble method that leverages multiple decision trees and randomization to improve generalization.
3. Ensemble Extra Tree: Similar to Random Forest but with additional randomization in the decision tree construction process.

3.5. Validation Model Performance:

Upon training the ensemble model, validated its performance becomes crucial. This is achieved by testing the model on a distinct dataset or employing methods like cross-validation. Performance metrics such as Precision, Accuracy, F1-Score, and Recall are computed to gauge the model's ability to predict Mesothelioma cases effectively.

3.6. Interpreting Results:

The final phase involves analyzing the results and deriving meaningful insights from the model's performance. This analysis may entail identifying key features, understanding the model's strengths and weaknesses, and potentially offering insights into predicting or diagnosing Mesothelioma based on the dataset.

4. Results and Discussion

Experimental setup is conducted using Python, with utilizing scikit-learn for ensemble learning and pandas, NumPy for efficient data cleaning and preprocessing. This approach ensured robust model construction and reliable evaluation for classifying Mesothelioma cancer.The Lung Cancer dataset available on Kaggle is a comprehensive collection of structured data pertaining to patients with lung cancer. It includes details such as patient demographics, clinical histories, diagnostic information, and treatment records. This dataset is a valuable resource for researchers and healthcare professionals alike, offering opportunities for detailed analysis, predictive modeling, and support for clinical decision-making regarding lung cancer. Its potential applications range from advancing cancer research and enhancing diagnostic precision to supporting public health efforts aimed at reducing the prevalence of lung cancer. However, users must exercise caution regarding data quality, addressing missing values, and considering ethical implications to ensure the accuracy and integrity of research conducted using this dataset within the field of lung cancer.

	age	gender	city	asbestos exposure	type of MM	duration of asbestos exposure	diagnosis method	keep side	cytology	duration of symptoms	...
0	47.0	1	0	1	0.0	20.0	1	0	1	24.0	...
1	55.0	1	0	1	0.0	45.0	1	0	0	1.0	...
2	29.0	1	1	1	0.0	23.0	0	1	0	1.0	...
3	39.0	1	0	1	0.0	10.0	1	0	0	3.0	...
4	47.0	1	0	1	0.0	10.0	1	1	1	1.5	...
...	...	...	...	...	...	...	...	...	...	...	...
319	75.0	1	1	1	0.0	50.0	1	1	0	9.0	...
320	66.0	1	1	1	0.0	41.0	1	1	0	9.0	...
321	58.0	1	6	1	0.0	40.0	1	0	0	8.0	...
322	42.0	1	6	0	0.0	0.0	0	1	0	2.0	...
323	54.0	1	0	1	0.0	40.0	1	1	0	3.0	...

324 rows × 35 columns

Figure 2. Dataset Reading

Figure 2 displays a dataset with 324 rows and 35 columns, containing various attributes related to patient demographics and medical history. Key columns include age, gender, city, asbestos exposure, type of mesothelioma (MM), duration of asbestos exposure, diagnosis method, and duration of symptoms.

```
[ ] df['class of diagnosis'] = df['class of diagnosis'].replace(2, 0)
```

```
X=df.drop(['class of diagnosis'],axis=1)
y=df['class of diagnosis']
print(X.shape,y.shape)
```

```
(324, 34) (324,)
```

Figure 3. Pre-Process

Figure 3 shows a data preprocessing step in Python using pandas. It modifies the 'class of diagnosis' column, replacing values of 2 with 0. Then, it separates the dataset into features (X) by dropping the 'class of diagnosis' column and labels (y) containing only the 'class of diagnosis' column. The shapes of X and y are printed, confirming that X has 324 rows and 34 columns, while y has 324 rows.

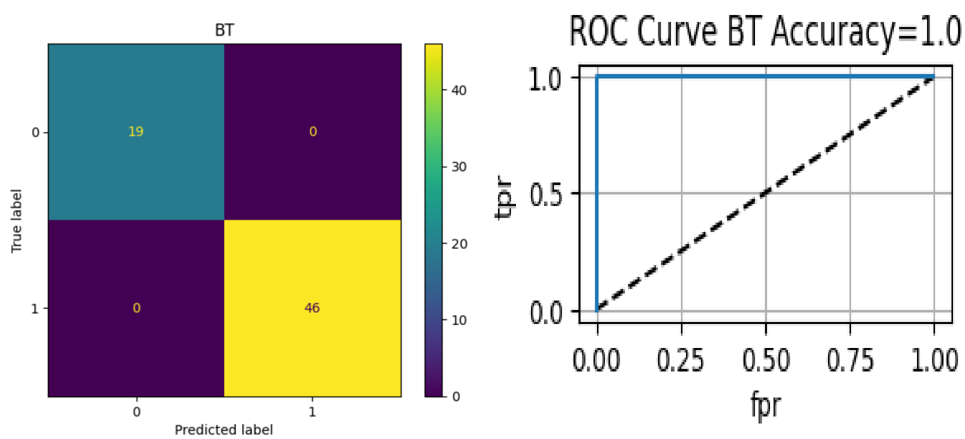

Figure 4. Testing Bagging Tree

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	46
accuracy			1.00	65
macro avg	1.00	1.00	1.00	65
weighted avg	1.00	1.00	1.00	65

Figure 5. Parameters of Bagging Tree

Figures 4 and 5illustrate the performance of a Bagging Tree model on a test dataset, showcasing a confusion matrix and an ROC curve with an accuracy of 1.0. The classification report demonstrates perfect precision, recall, and f1-scores for both classes, indicating flawless model performance on the test set.

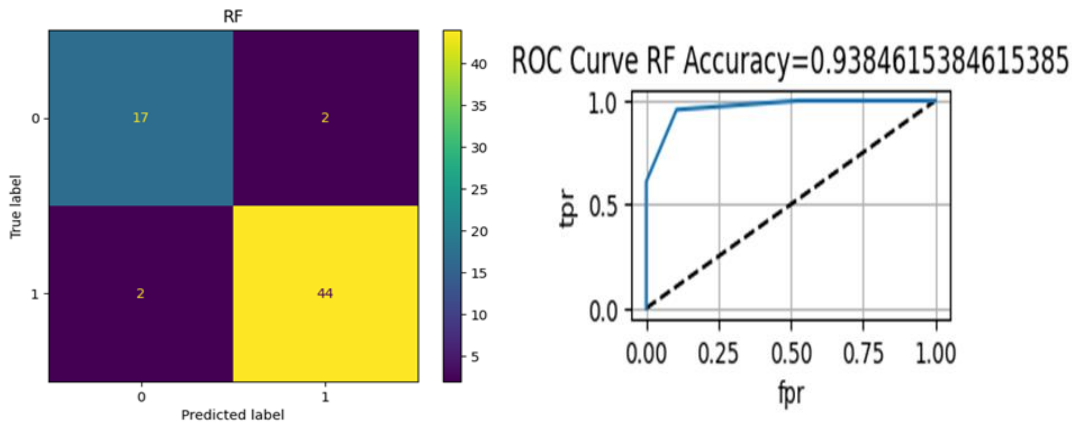

Figure6. Testing Random Forest

	precision	recall	f1-score	support
0	0.89	0.89	0.89	19
1	0.96	0.96	0.96	46
accuracy			0.94	65
macro avg	0.93	0.93	0.93	65
weighted avg	0.94	0.94	0.94	65

Figure 7. Parameters of Random Forest

Figures6 and 7 illustrate the performance of a Random Forest model on a test dataset, showcasing a confusion matrix and an ROC curve with an accuracy of 0.93.

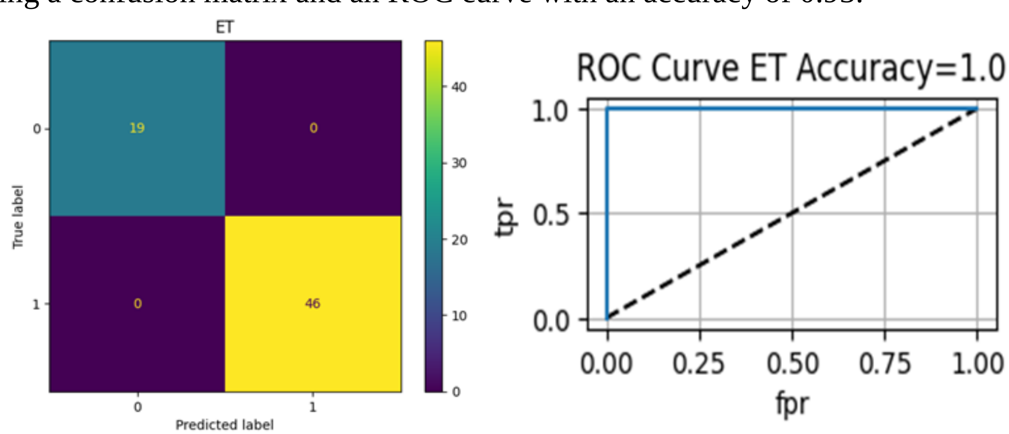

Figure8. Testing Ensemble Extra Tree

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        46

    accuracy                           1.00        65
   macro avg       1.00      1.00      1.00        65
weighted avg       1.00      1.00      1.00        65
```

Figure9. Parameters of Ensemble Extra Tree

Figures8 and 9 illustrate the performance of aExtra Tree model on a test dataset, showcasing a confusion matrix and an ROC curve with an accuracy of 1.0.The classification report demonstrates perfect precision, recall, and f1-scores for both classes, indicating flawless model performance on the test set.

Table 1. Models Evaluation

Models	**ACC (%)**	**P (%)**	**R (%)**	**F1 (%)**
Ensemble Extra Tree	99%	99%	99%	99%
Random Forest	93%	93%	93%	94%
Bagging Tree	99%	99%	99%	99%

Table 1 summarizes the performance evaluation metrics of different models:

- Ensemble Extra Tree and Bagging Tree both achieve high accuracy, precision, recall, and F1 score of 99% across the board.
- Random Forest shows slightly lower but still respectable performance with 93% accuracy, precision, recall, and a slightly higher F1 score of 94%.

5. Conclusion

The research presented in the article emphasizes the integration of ensemble classifiers with the Recursive Attribute Elimination (RAE) technique to enhance the classification accuracy of Mesothelioma Cancer. The study involves a comprehensive evaluation of various ensemble models, each showcasing distinct performance levels. For instance, the Bagging Tree model demonstrates robust equilibrium with a 99% accuracy rate, alongside 99% precision, recall, and an F1-Score, highlighting its adeptness in managing the precision-recall trade-off. In contrast, the Random Forest model consistently delivers solid outcomes, maintaining a stable 93% across accuracy, precision, recall, and an F1-Score of 94%. The Ensemble Extra Tree model emerges as the standout performer with exceptional metrics: 99% accuracy, precision, recall, and an impressive F1-Score of 99%.While the findings underscore the potential of ensemble techniques in enhancing diagnostic precision for Mesothelioma Cancer, a more nuanced interpretation is necessary. The article could benefit from acknowledging potential variations in performance across different datasets or clinical settings, which could impact the generalizability of the results. Moreover, while ensemble methods show promise in improving cancer detection and treatment outcomes, further validation and exploration in diverse clinical scenarios are crucial. By enhancing our understanding of these techniques in medical diagnosis, this research contributes significantly to advancing patient care, providing clinicians with more accurate tools for detecting and managing Mesothelioma Cancer effectively. Continued research and application of ensemble approaches hold promise for further optimizing cancer diagnostic processes and ultimately improving patient outcomes in clinical practice.

Compliance with Ethical Standards:
Funding: No funding was received for conducting this study.
Conflict of Interest: No Conflict of Interest.
Ethical approval: We would like to emphasize that this research did not involve the use of human or animal subjects. As a result, ethical approval from an institutional review board (IRB) or ethics committee was not required for this work.
Data availability: Not applicable.

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