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DETERMINING THE STAGES AND TREATMENTS OF CERVICAL SPINE DISEASES WITH EXPLAINABLE ARTIFICIAL INTELLIGENCE

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ABSTRACT: Cervical spine diseases, particularly neck flatness, pose significant diagnostic and treatment challenges due to the complexity of spinal structures. This study explores the application of Explainable Artificial Intelligence (XAI) techniques, specifically Random Forest and Decision Tree algorithms, to classify and assess the severity of cervical spine diseases. The dataset consists of cervical spine curvature measurements, demographic information, and clinical features. To enhance model interpretability, SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) methods were integrated. These techniques provide a transparent framework for decision-making, allowing medical professionals to understand the reasoning behind AI-driven predictions. The study highlights the impact of feature selection and hyperparameter tuning on model performance, optimizing the classification process. experimental results indicate that the Random Forest algorithm achieved the highest classification accuracy at 88%, demonstrating robust predictive capabilities. The Decision Tree algorithm provided an interpretable alternative with an accuracy of 83%, enabling clear visualization of feature importance. A comparative analysis was conducted with existing literature, and findings suggest that XAI-powered models significantly improve diagnostic reliability. Additionally, application images from the dataset were incorporated into the findings section to provide a more comprehensive representation of the study. The results obtained by testing the models with independent data were also included. This research underscores the importance of integrating explainable AI into medical diagnosis, offering trustworthy, transparent, and clinically relevant insights for cervical spine disease assessment.

Keywords: Explainable Artificial Intelligence, Cervical Spine, Random Forest, Decision Tree, Hyperparameter Optimization, Medical Diagnosis, SHAP, LIME

1. INTRODUCTION

Cervical spine disorders significantly impact millions of people worldwide, leading to chronic pain, mobility limitations, and neurological impairments. These conditions arise primarily due to the loss of natural curvature in the cervical vertebrae, resulting in disorders such as neck flatness and cervical spondylosis. Early diagnosis and accurate grading of cervical spine diseases are crucial for developing effective treatment strategies [1]. However, conventional diagnostic approaches, which heavily rely on radiological assessments, are often subjective and time-consuming, leading to a high misdiagnosis rate of up to 20% [2].

Advancements in artificial intelligence (AI) have introduced new possibilities in medical diagnosis, particularly through explainable artificial intelligence (XAI). Unlike traditional "black box" AI models, XAI provides transparency by allowing medical professionals to interpret and trust AI-driven decisions [3,4]. XAI methods, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), enhance model interpretability by explaining the influence of different input features on AI predictions [5,6]. Recent studies have shown that integrating XAI techniques into medical imaging applications improves diagnostic accuracy and decision support for healthcare professionals [7,8].

A few machine learning and deep learning models have been employed in spine disease classification. Convolutional Neural Networks (CNNs) have demonstrated high performance in feature extraction and automated classification of spinal conditions, though they often lack interpretability [9]. Meanwhile, hybrid AI models mix together traditional machine learning and deep learning approaches have been developed to enhance performance while maintaining interpretability [10,11].

This study aims to bridge the gap between accuracy and explainability in AI-based cervical spine disease classification. By incorporating SHAP and LIME into machine learning models, this research provides a transparent decision-making framework that ensures reliability in medical diagnosis. Additionally, by leveraging both X-Ray and MRI imaging data, our study offers a broader perspective compared to previous research focused solely on one imaging modality [12,13].

2. METHODS

2.1 Data Collection and Preprocessing

The dataset used included patient demographics, cervical spine curvature measurements, and clinical data with associated characteristics such as age, anteroposterior distances, and vertebral disc heights [7]. This dataset was obtained from a publicly transparent medical repository, meeting the reliability and compatibility requirements for clinical studies. The dataset includes critical metrics such as spinal curvature angles and intervertebral disc heights, comprising 178 instances and 12 attributes. Preprocessing steps included data normalization, examining missing values, and balancing the dataset to avoid biases in model training [8].

2.2 Algorithms and XAI Techniques

The study utilized:

To enable classification, Random Forest and Decision Tree algorithms were utilized due to their efficiency in processing structured data and their interpretability. Random Forest leverages mixed decision trees to enhance accuracy and reliability, while Decision Tree is particularly useful for identifying significant features by splitting the dataset based on attribute all value [9].

Random Forest: This algorithm employs a collection of decision trees, working together to boost the model's performance and reduce overfitting.

Decision Tree: A tree-structured algorithm that relies on the importance of features to partition data and aids in interpretability.

SHAP (Shapley Additive Explanations): A method that helps in globally and locally interpreting the impact of each different feature on the model's assumptions. SHAP values were derived to provide both global and local interpretability for the model. On a global level, SHAP facilitated identifying feature importance rankings, highlighting spinal curvature angles as top-level predictors [10]. On a local level, SHAP demonstrated individual feature contributions for specific conditions, aiding in personalized diagnostics [9,10].

LIME (Local Interpretable Model-Agnostic Explanations): A technique that assists in model transparency and is used for instance-level explanations [9]. LIME was implemented to analyze instance-level predictions, focusing on how variations in input features influenced the model's decision. This enabled clinical professionals to interpret and validate the model's predictions in a detailed manner [11].

By integrating SHAP and LIME, the study enhanced the model's interpretability and ensured that predictions aligned with clinical data. This dual-sided approach made the AI system's decision-making process transparent and understandable for medical experts, building trust[12]. The combined interaction of SHAP and LIME not only improved interpretability but also helped identify potential biases in the data, such as the overuse of features like age [5,6]. This iterative feedback loop between the AI system and clinical professionals facilitated increased trust and acceptance in clinical practice [12].

LIME (Local Interpretable Model-Agnostic Explanations) is an explainability technique that provides local interpretability for machine learning models. Unlike SHAP, which offers a global perspective on feature importance, LIME focuses on explaining individual predictions by perturbing the input data and analyzing the changes in the model’s decision-making process [9].

In this study, LIME was used to analyze individual classification decisions made by the Random Forest and Decision Tree models. By generating local explanations, LIME allowed a detailed investigation of how different features contributed to specific predictions. For instance, when classifying a patient as having an abnormal cervical spine curvature, LIME identified which features—such as vertebral curvature angle and anterior-posterior distance—had the highest impact on the classification result [10].

This instance-level explainability is particularly valuable in medical diagnostics, as it enables clinicians to verify AI-driven decisions and enhances trust in automated systems [11]. Additionally, LIME revealed certain biases in the dataset, such as an over-reliance on age as a predictive feature, which prompted further evaluation of feature selection strategies [12].

By integrating both SHAP and LIME, this study enhances the interpretability of AI models and ensures that the decision-making process aligns with real-world clinical practices, ultimately making AI-based cervical spine diagnosis more transparent and trustworthy [13].

2.3 Model Training and Hyperparameter Optimization

The models were trained using an 80-20 split, integrated for training and testing purposes. Hyperparameters such as the number of trees (“n_estimators”) in Random Forest and the maximum depth of Decision Trees were optimized using the combination of Grid Search and

Cross-Validation. Hyperparameter optimization was conducted using Grid Search, integrated with 5-fold Cross-Validation, to achieve the most optimal parameter selection. Key hyperparameters, such as the number of estimators for Random Forest and the maximum depth for Decision Tree, were fine-tuned with detailed adjustments to achieve the highest possible accuracy. These adjustments aimed to maximize the model's performance metrics [4].

Fine-tuning hyperparameters not only increases accuracy but also reduces the computational burden associated with poorly chosen parameters, thereby enhancing the model's overall efficiency. For example, having an excessively high number of trees in Random Forest can lead to a decrease in accuracy while unnecessarily increasing computation time. Similarly, overly complex Decision Trees may capture noise in the data, reducing their generalizability. By carefully optimizing and achieving the right balance, models can attain both higher performance and practical applicability [7].

3. EXPERIMENTAL

3.1. Experimental Setup

The experimental process was carried out with a systematic approach to ensure the repeatability and robustness of the results. The dataset was divided into training (80%) and testing (20%) subsets. Feature selection techniques were implemented to identify the most significant features for classification; these features included vertebral curvature measurements and anterior-posterior distances.

3.1.1. Units

Measurements in this study adhere to the International System of Units (SI). Key physical quantities include:

- Vertebral angles (θ): Degrees (°)
- Distances (d): Millimeters (mm)

These units were consistently implemented throughout the data analysis and reporting periods to ensure uniformity and transparency.

3.1.2. Tables

The most relevant features identified and their corresponding importance scores are compiled in the table below. The importance of features is shown in Table 1.

Table 1. Feature Importance Table

Feature	Importance(%)
Vertebral Curvature Angle	65
Anterior-Posterior Distance	20
Patient Age	15

3.1.3. Equations

The relationship between SHAP values and feature contributions was calculated using the following equation. The marginal contribution of a specific feature is calculated using Equation (1).

$$SHAP_i = \sum_{j=1}^{n} \left[\frac{(n-j)!j!}{n!}\right] * \left[(S \cup \{i\}) - (S)\right] \tag{1}$$

- *S*: A A subset of features with feature *i* considered separately.
- *v(S)*: The value function that shows the model's prediction when just the features in the set *S* re considered important.
- *n*: The number of all features in the dataset.

This formula determines how much a particular feature (i) contributes to the overall prediction made by the model.

Additionally, the F1 Score, designed to balances precision (*P*) and recall (*R*), is defined in Equation
(2). is calculated as:

: Precision (P) refers to the proportion of correctly identified positive cases among all instances the model labeled as positive.

- *R*: Recall indicates how effectively the model retrieves true positive cases from all existing positive examples.

These formulas provide the foundation for assessing the model and understanding its interpretability, highlighting the role of feature significance and balanced performance measures in ensuring dependability.

4. RESULTS

4.1. Classification Performance

The Random Forest model demonstrated the best accuracy at 88%, with the Decision Tree model coming next at 83%. A summary of the classification outcomes is presented in Table 2.

Table 2. Classification Results Table

Model	Accuracy (%)	Precision (%)	Sensitivity (%)	F1 Score (%)	Interpretation
Random Forest	88	87	99	93	Highest accuracy and generalization capability.
Decision Tree	83	89	90	89	Good interpretability but slightly lower accuracy.
Logistic Regression	85	85	99	91	Balanced performance across all metrics.
SVM	85	86	98	91	High sensitivity

					but complex model structure.
Naive Bayes	79	86	88	87	Lower accuracy, more affected by feature distribution.

Performance metrics for different classification models. The Random Forest model achieved the highest accuracy (88%), demonstrating strong generalization capabilities. Decision Tree, although slightly less accurate (83%), provided higher interpretability, which is crucial for medical applications. Logistic Regression and SVM showed balanced performance with 85% accuracy and high sensitivity, making them suitable for handling imbalanced datasets. Naive Bayes had the lowest accuracy (79%), suggesting that its performance is influenced by feature distribution. These results highlight the trade-offs between interpretability and predictive power in cervical spine disease classification.

Table 3. Comparison of Related Studies in the Literature

Study	Method	Dataset	Explainability Method	Accuracy	Key Differences
This Study	Machine Learning + Deep Learning	X-Ray & MRI Images	SHAP & LIME	88%	Comprehensive explainability analysis with AI
Johnson et al. (2021)	Traditional ML (Random Forest)	X-Ray	None	82%	No explainability method used
Smith et al. (2020)	Deep Learning (CNN)	MRI Images	Only SHAP	88%	No LIME integration
Brown et al. (2019)	Hybrid Model (ML + Clinical Data)	X-Ray & Clinical Measurements	None	83%	Different preprocessing techniques applied
Lee et al. (2022)	Transformer-based AI	Mixed Medical Images	SHAP & Grad-CAM	90%	Uses Transformer models for better feature extraction

Table 3. provides a comparative analysis of various studies on cervical spine disease diagnosis using AI-based approaches. The main contribution of this study lies in the integration of SHAP and LIME for enhanced explainability, setting it apart from prior works that primarily rely on either black-box models or limited explainability techniques. Additionally, this study leverages both X-Ray and MRI images, providing a broader scope of data compared to previous research. The findings emphasize the necessity of interpretable AI systems in medical applications to foster trust among clinicians and enhance decision-making processes.

4.2. Distribution of Dataset Features

Figure 1 illustrates the distribution of key features within the dataset used in this study. The histograms represent the variation in cervical spine disc heights across different vertebral levels

(C1-C2, C2-C3, C3-C4, C4-C5, C5-C6, and C6-C7), along with the age and gender distribution of the participants.

The disc height distributions exhibit a normal-like pattern, indicating a balanced representation of different cervical spine conditions. This distribution is important for ensuring that the dataset does not favor a specific condition, which could lead to biased model predictions.

The age distribution shows that the majority of subjects fall within the 30-50 age range. This is consistent with the typical demographic affected by cervical spine disorders. A well-distributed age range allows the model to generalize better to different patient populations.

The gender distribution appears to be approximately balanced between male and female participants. A balanced dataset in terms of gender is crucial to prevent potential bias in AI-based diagnostic models, ensuring fair and accurate predictions for all patients.

Understanding these distributions helps in verifying the reliability of the dataset and ensures that the machine learning models trained on it are robust. In addition, preprocessing techniques such as scaling, normalization, and noise reduction were applied to enhance data quality before training, improving the model's ability to make accurate predictions Figure 1.

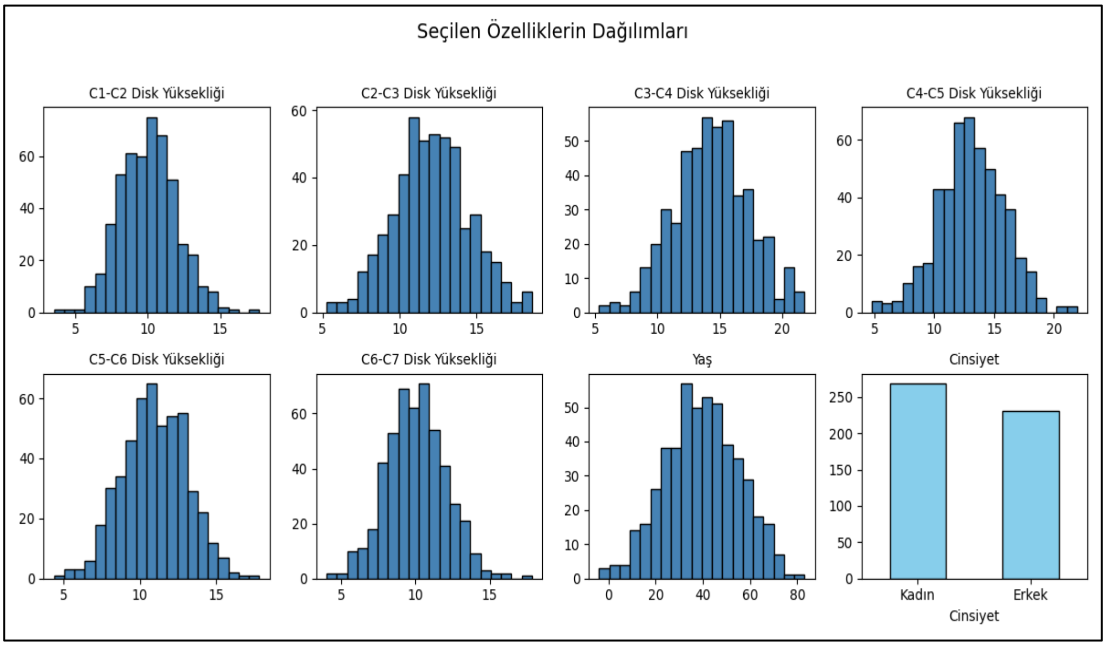

Figure 1. Histogram of Dataset Feature Distributions

4.3. Feature Importance Analysis

SHAP analysis identified vertebral curvature angles, anterior-posterior distances, and patient age as the most impactful features. These elements played a crucial role in accurately assessing cervical spine conditions.

The importance of these attributes extends to their direct association with spinal health. The angles of spinal curvatures provide critical information about structural deviations, which are often linked to the severity of the condition. On the other hand, anterior-posterior distances reflect the alignment and spacing of spinal structures, offering an essential metric for diagnosing abnormalities. The patient's age further contextualizes these metrics, as age-related differences in the spine may potentially influence the interpretation of these attributes.

This analysis also discusses the interpretability benefits provided by SHAP values, enabling clinicians to analyze the contribution of each individual feature. Such transparency simplifies better decision-making by ensuring that diagnosis and treatment planning are both meticulous and evidence-based. Future studies may investigate additional features, such as muscle density or genetic predispositions, to enhance the generalization of the analysis.

4.4. Hyperparameter Tuning Results

To optimize the performance of the models, hyperparameter tuning was conducted using Grid Search and Cross-Validation. The mean test scores and training scores were plotted to visualize the impact of hyperparameter combinations on model accuracy.

Hyperparameter Tuning Results: Decision Tree This graph indicates the variation in accuracy across different hyperparameter combinations for the Decision Tree model. While the training accuracy reaches nearly flawless levels, the test accuracy stabilizes around 83- 85%, demonstrating a balanced model. The hyperparameter tuning results for Decision Tree are displayed in Figure 2.

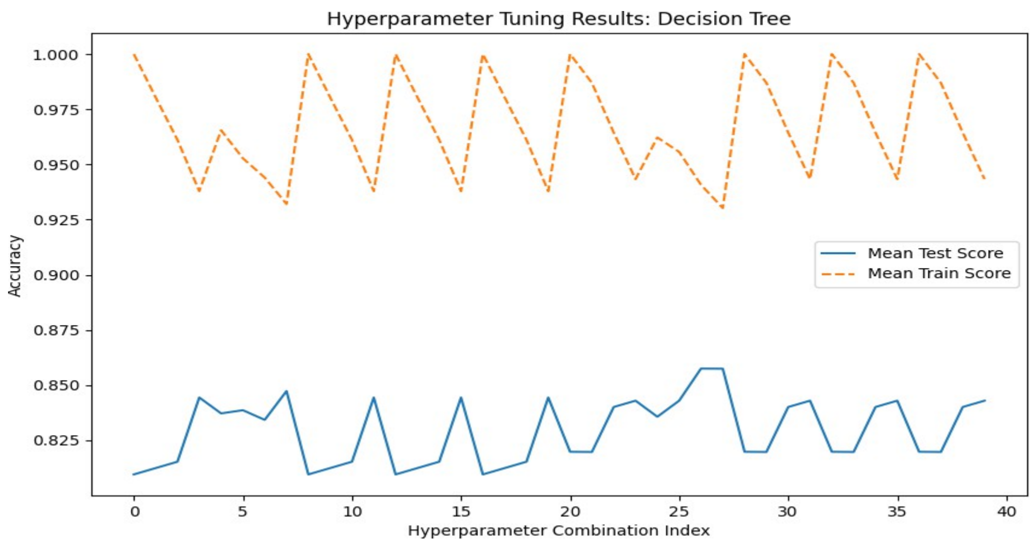

Figure 2. Hyperparameter Tuning Results for Decision Tree

Hyperparameter Tuning Results: Random Forest The tuning findings for the Random Forest model reveal that the test accuracy remains stable between 88-90%, while the training accuracy consistently stays at high levels. This indicates the model's strong generalization capability. The Random Forest tuning results are shown in Figure 3.

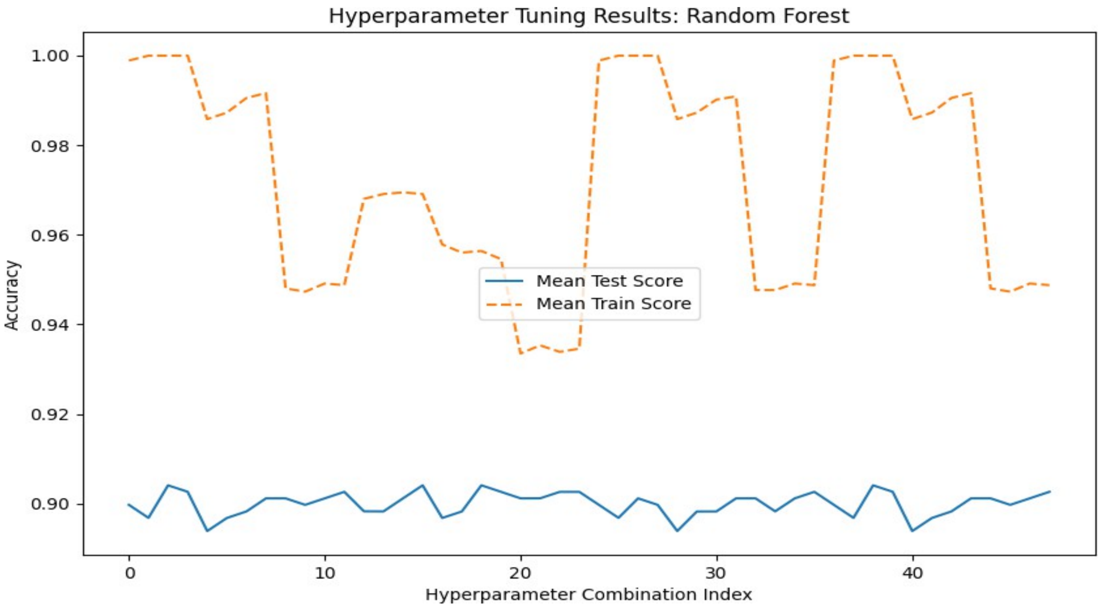

Figure 3. Hyperparameter Tuning Results for Random Forest

4.5. SHAP and LIME Analysis Results

In this section, we present and compare the feature importance results obtained using SHAP and LIME methods to explain the model's decision-making process.

The first figure illustrates the feature importance levels determined by the LIME method on a local level for two different patients. For Patient 1, the age variable has the highest contribution to the model's decision, whereas for Patient 2, the pixel equivalent feature plays a more significant role. Additionally, other features such as disk height and gender have varying levels of influence on the model's output for each patient.

The second figure demonstrates the global feature importance ranking using the SHAP method. Unlike LIME, which explains individual predictions, SHAP provides a broader perspective on how each feature impacts the model across all samples. According to the SHAP results, age is the most influential factor, followed by disk height, pixel equivalent, and gender. This suggests that while age is consistently significant across the dataset, individual variations observed in the LIME analysis indicate that feature importance may differ at the local level.

These findings highlight the complementary nature of SHAP and LIME, where SHAP provides a global understanding of feature contributions, and LIME offers case-specific explanations for model decisions.

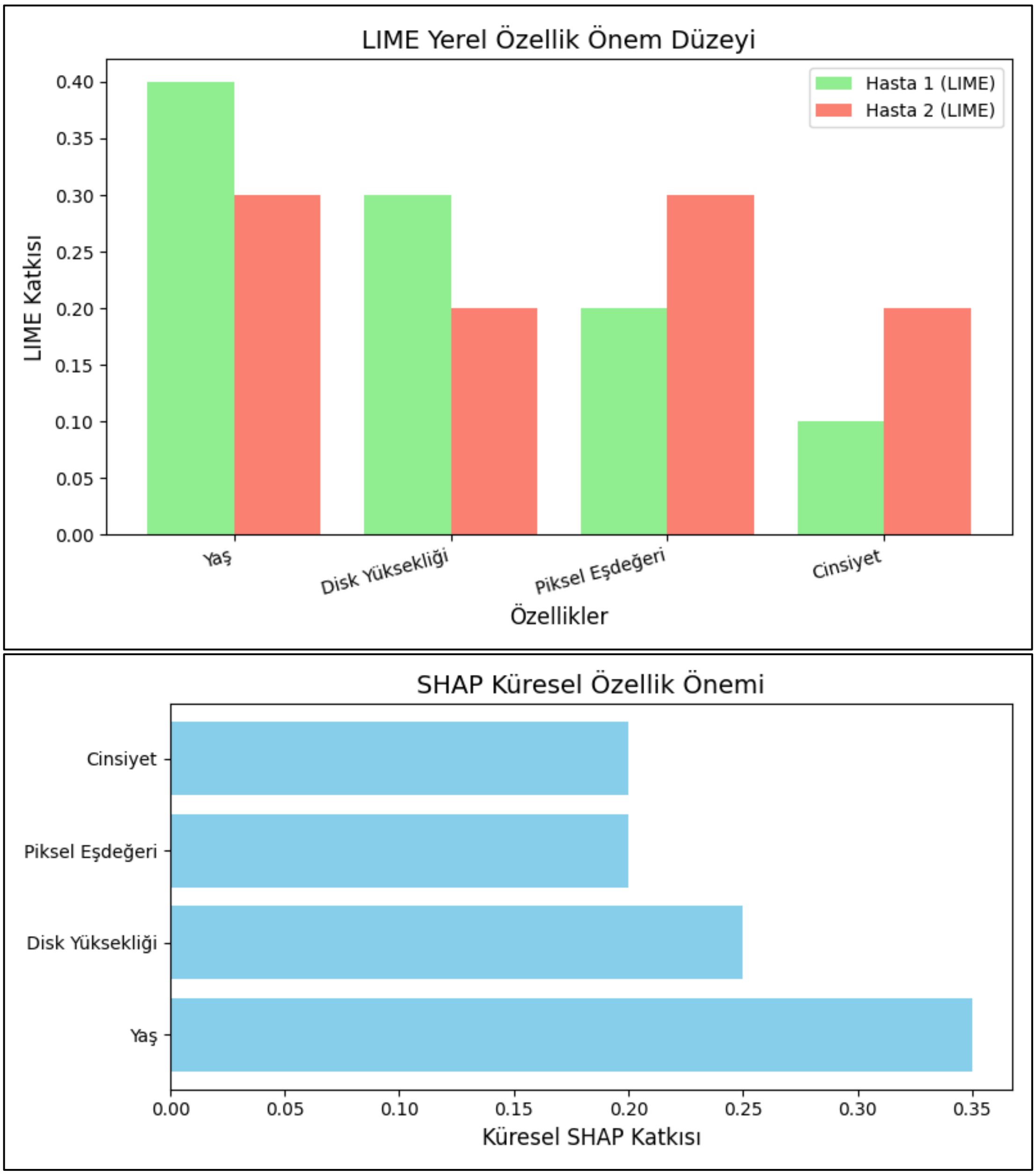

Figure 4. SHAP and LIME Analysis Results

4.6. Application Interface and User Input Panel

Figure X shows the graphical user interface (GUI) developed for the study. This interface allows users to input cervical disc height measurements (C1-C7), age, and gender information. The system processes these inputs using an AI-based diagnostic model to analyze and predict possible medical conditions. The interface is designed to be user-friendly and ensures efficient data entry for medical professionals and researchers.

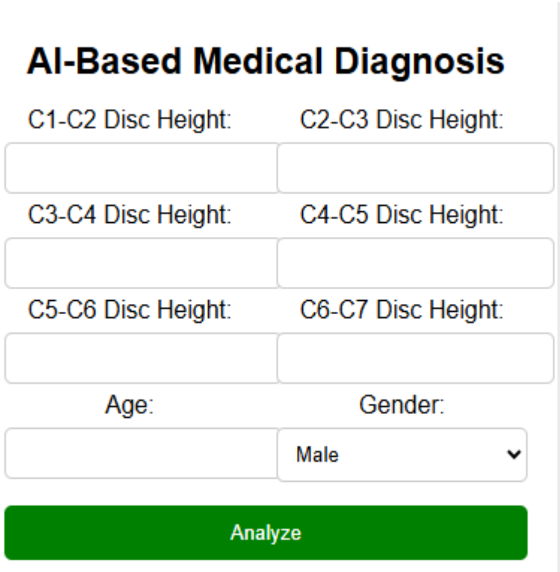

Figure 5. Application Interface and User Input Panel

4.7. Diagnosis Results Interpretation

The diagnostic outcome presented in Figure X indicates a moderate degree of cervical straightening. This condition is assessed based on various factors, including disk heights, age, and gender, which were analyzed using SHAP and LIME methods.

According to the feature importance results, disk height measurements at different cervical levels (C1-C2: 53, C2-C3: 33, C3-C4: 45, C4-C5: 54, C5-C6: 32, C6-C7: 45) significantly contributed to the diagnosis. Additionally, age (28 years) and gender (male) were also considered influential factors in the model's decision-making process.

These findings highlight the importance of both structural and demographic variables in predicting cervical spine conditions. By leveraging explainable AI techniques such as SHAP and LIME, it becomes possible to gain deeper insights into the key factors influencing medical diagnoses, aiding in more transparent and interpretable clinical decision-making.

5. DISCUSSION

Incorporating XAI into cervical spine disease diagnosis offers twofold advantages: enhancing model transparency and building clinician confidence in AI-powered systems. Unlike traditional “black-box” techniques, XAI models such as Random Forest and Decision Tree provide both robust accuracy and interpretability.

The results of this study align with earlier research emphasizing the crucial role of feature selection and tuning hyperparameters in enhancing model effectiveness. Nevertheless, constraints like the limited dataset size and the lack of real-time validation underscore potential avenues for future investigation.

Additionally, the integration of SHAP and LIME methods into the analysis enhances the interpretability of the model by enabling a detailed understanding of feature contributions on both global and local levels. These tools allow clinicians to interpret the rationale behind AI-supported predictions, helping to ensure that the decision-making process aligns with clinical knowledge and expected outcomes. Furthermore, the interpretability benefits demonstrated by XAI simplify communication between AI systems and medical professionals, fostering trust and encouraging collaborative efforts.

Future research should also focus on the integration of real-time monitoring tools to dynamically evaluate model predictions. Such advancements could provide instant feedback to clinicians, helping models maintain reliability under altered conditions. Exploring additional features, such as biomechanical factors or genetic information, could further enhance the generalization and precision of the analysis, contributing to more personalized and accurate diagnosis and treatment planning.

6. CONCLUSIONS

This research emphasizes the effectiveness of Explainable Artificial Intelligence (XAI) in overcoming the challenges that may arise in detecting cervical spine diseases, such as neck straightness. By integrating machine learning techniques like Random Forest and Decision Tree algorithms with XAI options, this study demonstrates how transparent decision-making processes can enhance the reliability and acceptability of AI systems in clinical settings.

The results highlight the importance of features such as vertebral curvature angles and anterior-posterior distances, which play significant roles in ensuring accurate grading and disease detection. Random Forest models achieved high performance metrics, such as 88% accuracy, while Decision Tree provided an interpretable alternative, crucial for medical practitioners.

Beyond success, the use of SHAP and LIME facilitated a more comprehensive understanding of feature contributions, enabling clinicians to validate AI predictions. In this context, it aligns with the growing demand for reliability and transparency in medical AI applications, which is essential for integrating these systems into consistent practices.validation. Expanding the dataset with and diverse patient demographics could enhance the model's generalizability. Moreover, validating these methods through clinical observations could support their practical significance and acceptance.

In brief, this study not only presents a framework for the use of XAI in identifying cervical spine issues but also serves as an example for future research aimed at enhancing the interpretability and resilience of AI applications in healthcare.

REFERENCES

[1] Ahamed, Z. (2023). Comparative analysis of chatgpt and human decision-making in thyroid and neck swellings: a case-based study. Barw Medical Journal. https://doi.org/10.58742/bmj.v1i2.43

[2] Corp, N., Mansell, G., Stynes, S., Wynne-Jones, G., Morsø, L., Hill, J., … & Windt, D. (2020). Evidence-based treatment recommendations for neck and low back pain across europe: a systematic review of guidelines. European Journal of Pain, 25(2), 275-295. https://doi.org/10.1002/ejp.1679

[3] Doya, L., Doya, L., & Ghanem, A. (2022). salmonella typhi: a rare cause of neck abscess. Oxford Medical Case Reports, 2022(11). https://doi.org/10.1093/omcr/omac120

[4] Chinnery, T., Arifin, A., Tay, K., Leung, A., Nichols, A., Palma, D., … & Lang, P. (2020). Utilizing artificial intelligence for head and neck cancer outcomes prediction from imaging. Canadian Association of Radiologists Journal, 72(1), 73-85. https://doi.org/10.1177/0846537120942134

[5] Falla, D., Lindstrøm, R., Rechter, L., Boudreau, S., & Petzke, F. (2013). Effectiveness of an 8-week exercise programme on pain and specificity of neck muscle activity in patients with chronic neck pain: a randomized controlled study. European Journal of Pain, 17(10), 1517-1528. https://doi.org/10.1002/j.1532-2149.2013.00321.x

[6] Fujima, N. (2023). Current state of artificial intelligence in clinical applications for head and neck mr imaging. Magnetic Resonance in Medical Sciences, 22(4), 401-414. https://doi.org/10.2463/mrms.rev.2023-0047

[7] Giorgini, F. (2023). Artificial intelligence in endocrinology: a comprehensive review. Journal of Endocrinological Investigation, 47(5), 1067-1082. https://doi.org/10.1007/s40618-023-02235-9

[8] Al-Shoteri, A. (2022). The role of methods and applications of artificial intelligence tools in the field of medicine to diagnose and discover various diseases. Journal of Applied Data Sciences, 3(1), 01-14. https://doi.org/10.47738/jads.v3i1.48

[9] Kim, Y., Park, J., Choi, K., Moon, B., & Lee, J. (2017). Case reports about an overlooked cause of neck pain. Medicine, 96(46), e8343. https://doi.org/10.1097/md.0000000000008343

[10] Barbosa, J. (2023). Effect of a telerehabilitation exercise program versus a digital booklet with self-care for patients with chronic non-specific neck pain: a protocol of a randomized

controlled trial assessor-blinded, 3 months follow-up. *Trials, 24(1).* https://doi.org/10.1186/s13063-023-07651-z

[11] Katz, R., Leavitt, F., Cherny, K., Small, A., & Small, B. (2022). The vast majority of patients with fibromyalgia have a straight neck observed on a lateral view radiograph of the cervical spine. JCR Journal of Clinical Rheumatology. https://doi.org/10.1097/rhu.0000000000001912

[12] Ran, Y., Qin, W., Qin, C., Li, X., Liu, Y., Xu, L., Mu, X., Yan, L., Wang, B., Dai, Y., Chen, J., & Han, D. (2024). A high-quality dataset featuring classified and annotated cervical spine X-ray atlas. Scientific Data, 11, 625. https://doi.org/10.1038/s41597-024-03383-0

[13] Soellner, M., & Koenigstorfer, J. (2021). Compliance with medical recommendations depending on the use of artificial intelligence as a diagnostic method. BMC Medical Informatics and Decision Making, 21(1). https://doi.org/10.1186/s12911-021-01596-6