Type of the Paper (Article, Review, Communication, etc.)

XAI For ChessAI

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**Abstract:** This project investigates the application of Explainable Artificial Intelligence (XAI) techniques to enhance the transparency and understanding of a chess AI system. The primary objective is to develop a chess AI that not only performs at a high level but also provides detailed explanations of its decisions, thereby improving user trust and engagement. Using a combination of SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations), the project created a model that interprets and visualizes the decision-making process of the chess AI. The chess AI was trained using features extracted from various game states, such as material advantage, center control, king safety, mobility, attack coverage, and defense stance. The Random Forest Regressor model was employed to predict the best move based on these features, with mobility identified as the most significant factor. The results demonstrate the efficacy of XAI methods in elucidating the AI's decision-making process, making it accessible and comprehensible to players. This integration of XAI into chess AI systems represents a significant advancement in the field, promoting transparency and trust in AI applications.

**Keywords:** Explainable Artificial Intelligence (XAI); Chess AI; SHAP; LIME; Machine Learning; Game Theory; Random Forest Regressor

1. Introduction

In an era where Artificial Intelligence (AI) permeates various facets of human life, from healthcare to autonomous vehicles, the realm of chess has emerged as a captivating domain for demonstrating AI's prowess. Chess, a game of immense complexity and strategic depth, has long been a benchmark for AI development. Since the historic victory of IBM's Deep Blue over world champion Garry Kasparov, the evolution of chess AI has been nothing short of remarkable. However, as these AI systems become more sophisticated, their decision-making processes often remain opaque, creating a 'black box' phenomenon that can undermine user trust and acceptance.

This project aims to bridge this transparency gap by integrating Explainable Artificial Intelligence (XAI) techniques into a high-performing chess AI system. The importance of this endeavor cannot be overstated, as it addresses the critical need for AI systems that are not only powerful but also interpretable and trustworthy. In recent years, the field of XAI has gained significant traction, with researchers striving to develop methods that can elucidate the inner workings of complex models. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have been at the forefront of this revolution, offering tools to dissect and visualize model decisions in a comprehensible manner.

The current landscape of XAI in chess AI is still nascent, with limited research exploring this intersection. Traditional chess engines, while highly effective, do not provide insights into their strategic choices, leaving players and enthusiasts in the dark about the rationale behind moves. This lack of transparency can be particularly challenging in educational contexts, where understanding the reasoning behind decisions is crucial for learning and improvement.

This study builds upon foundational work in both AI and XAI, drawing inspiration from key publications that have paved the way for explainable models. One such seminal work is by Lundberg and Lee (2017), which introduced SHAP as a unified framework for interpreting model predictions. Additionally, Ribeiro, Singh, and Guestrin's (2016) development of LIME has been instrumental in providing local fidelity explanations, making complex models more accessible to users.

Despite these advancements, there remain contentious debates within the field. One such controversy revolves around the balance between model complexity and interpretability. High-performing models often come with increased complexity, which can obscure their decision-making processes. Conversely, simpler models, while more interpretable, may sacrifice accuracy and performance. This project navigates this dichotomy by leveraging the strengths of SHAP and LIME to enhance the interpretability of a robust Random Forest Regressor model used for chess move prediction.

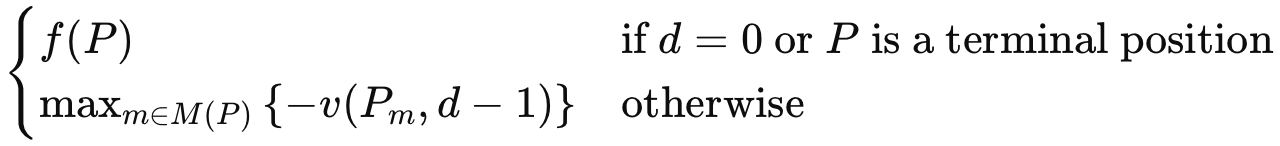
The primary aim of this work is to develop a chess AI that not only excels in performance but also provides detailed, interpretable explanations of its decisions. By extracting and analyzing features such as material advantage, center control, king safety, mobility, attack coverage, and defense stance, the study seeks to demystify the AI's strategic choices. The integration of XAI methods into the chess AI system offers a pioneering approach that enhances transparency, fosters trust, and promotes a deeper understanding of AI-driven strategies.

In conclusion, this project represents a significant step forward in the quest for explainable and trustworthy AI systems. By making the decision-making process of chess AI transparent and accessible, it not only advances the field of AI but also provides valuable tools for education and engagement in the world of chess. This fusion of XAI and chess AI heralds a new era of intelligent systems that are not only powerful but also comprehensible, fostering a symbiotic relationship between humans and machines.

2. Background Info

**Initial Approach: Random Move Selection:** The simplest approach to developing a Chess AI is to select moves randomly from the set of all valid moves. While this method ensures that the AI can make legal moves, it lacks any strategic depth or foresight, making it an inadequate opponent.

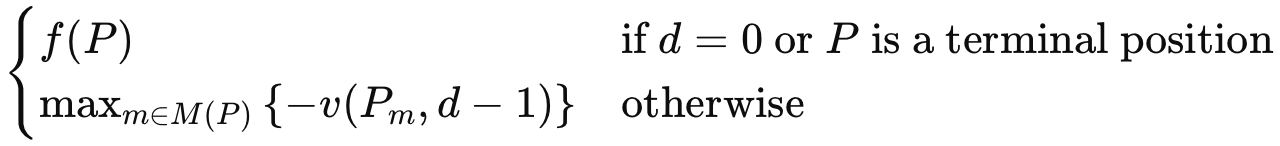
where P is the current position and ValidMoves(P) is the set of all valid moves from position P.

**Minimax Algorithm:** The next step in the evolution was the implementation of the Minimax algorithm, which evaluates positions to a fixed depth and assumes that both players play optimally. Minimax works by minimizing the possible loss for a worst-case scenario. The evaluation function f assesses the board state and assigns a score.

where:

* is the evaluation of position P at depth d.
* is the evaluation function that assesses the board state and assigns a score.
* is the set of all possible moves from position P.
* is the position resulting from move m.

The Minimax algorithm recursively explores all possible moves to a certain depth, alternating between minimizing and maximizing the evaluation based on whose turn it is to move.

**NegaMax Algorithm:** The NegaMax algorithm simplifies Minimax by utilizing the fact that . This symmetry allows a single recursive function to handle both maximizing and minimizing players.

Here, the max function and the negation handle the alternating nature of the game.

**NegaMax with Alpha-Beta Pruning:** Alpha-beta pruning enhances the NegaMax algorithm by eliminating branches in the search tree that do not need to be explored, significantly reducing the number of nodes evaluated.

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Description automatically generatedA black text on a white background

Description automatically generated**Alpha-beta pruning works by maintaining two values, alpha and beta, which represent the minimum score that the maximizing player is assured and the maximum score that the minimizing player is assured, respectively. If the current position's evaluation falls outside this range, further exploration of that branch is unnecessary.

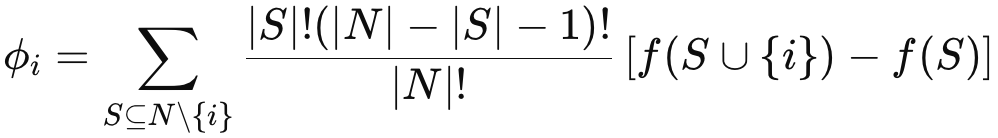
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Description automatically generated**Random Forest Regressor for Training Chess AI:** In the training phase, a Random Forest Regressor is employed to predict the quality of board positions based on extracted features. This method aggregates the predictions of multiple decision trees to enhance predictive performance and control overfitting. The prediction for an instance x is given by:

Where:

* is the number of trees in the forest.
* is the prediction of the tree for the input x.

Each tree in the forest is built using a different bootstrap sample of the training data, and random subsets of features are considered when splitting nodes, ensuring diversity among the trees.

**SHAP (Shapley Additive exPlanations):** SHAP values are based on Shapley values from cooperative game theory, providing a consistent method to attribute the impact of each feature on the model's predictions. For a given prediction, the SHAP value of a feature is calculated as:

where N is the set of all features, S is a subset of features, and f is the model's prediction function.

**LIME (Local Interpretable Model-agnostic Explanations):** LIME approximates the complex model locally around the prediction of interest by fitting a simple, interpretable model. It perturbs the input data and observes the changes in the output to understand the local decision boundary. The steps involved in LIME are: Perturbation, Prediction, Weighting, Fitting.

3. Literature Review

This literature review is conducted to understand the current state of Explainable Artificial Intelligence (XAI) and its various methodologies. This review is essential to contextualize our work, identify the strengths and limitations of existing approaches, and highlight the need for our proposed ChessXAI model. By examining prior research, we aimed to build on established knowledge, address identified gaps, and ensure that our model integrates the most effective XAI techniques. The literature review informs our approach and validates the necessity and potential impact of our research in advancing XAI in the domain of strategic decision-making in chess.

Feiyu Xu et al., in the research paper “Explainable AI: A Brief Survey on History, Research Areas, Approaches, and Challenges” (2019), present a detailed exploration of the evolution of Explainable Artificial Intelligence (XAI). The paper outlines key research areas, including model interpretability and user-centric explanations, and discusses various approaches such as post-hoc explanation techniques and transparent model designs. It emphasizes the importance of XAI in enhancing trust and accountability in AI systems while addressing challenges like balancing explanation quality with model performance and handling domain-specific requirements (Xu et al., 2019).

Taha Yasseri et al., in “Transparency and Artificial Intelligence: Towards Explanation in Intelligent Systems” (2019), explore the necessity of transparency in AI systems, focusing on methods to enhance user understanding of algorithmic decisions. The paper discusses techniques such as post-hoc explanations and visual interpretability tools while highlighting the societal implications of opaque AI systems, including issues of fairness and accountability (Yasseri et al., 2019).

Anastassia Angelopoulou et al., in “Explainable AI: Theory and Applications in Healthcare” (2021), focus on the role of explainability in AI systems within the healthcare domain. The paper covers theoretical frameworks and practical applications, emphasizing methods like saliency mapping and counterfactual explanations. It also addresses challenges such as ensuring explainability without compromising diagnostic accuracy (Angelopoulou et al., 2021).

Ramon López de Mántaras et al., in “Explainable Artificial Intelligence in Education: Challenges and Opportunities” (2022), provide an overview of XAI’s integration into educational technologies. The research discusses model-agnostic techniques, the use of pedagogical explanations for personalized learning, and the challenges of designing user-friendly explainable systems for educators and students (López de Mántaras et al., 2022).

Andreas Holzinger, in “Explainable AI (XAI): Concepts, Applications, and Challenges in Medical Informatics” (2018), delves into the application of XAI in medical decision-making. The paper examines model transparency and techniques like feature importance visualizations, stressing the balance between explainability and maintaining high-performance metrics in critical healthcare settings (Holzinger, 2018).

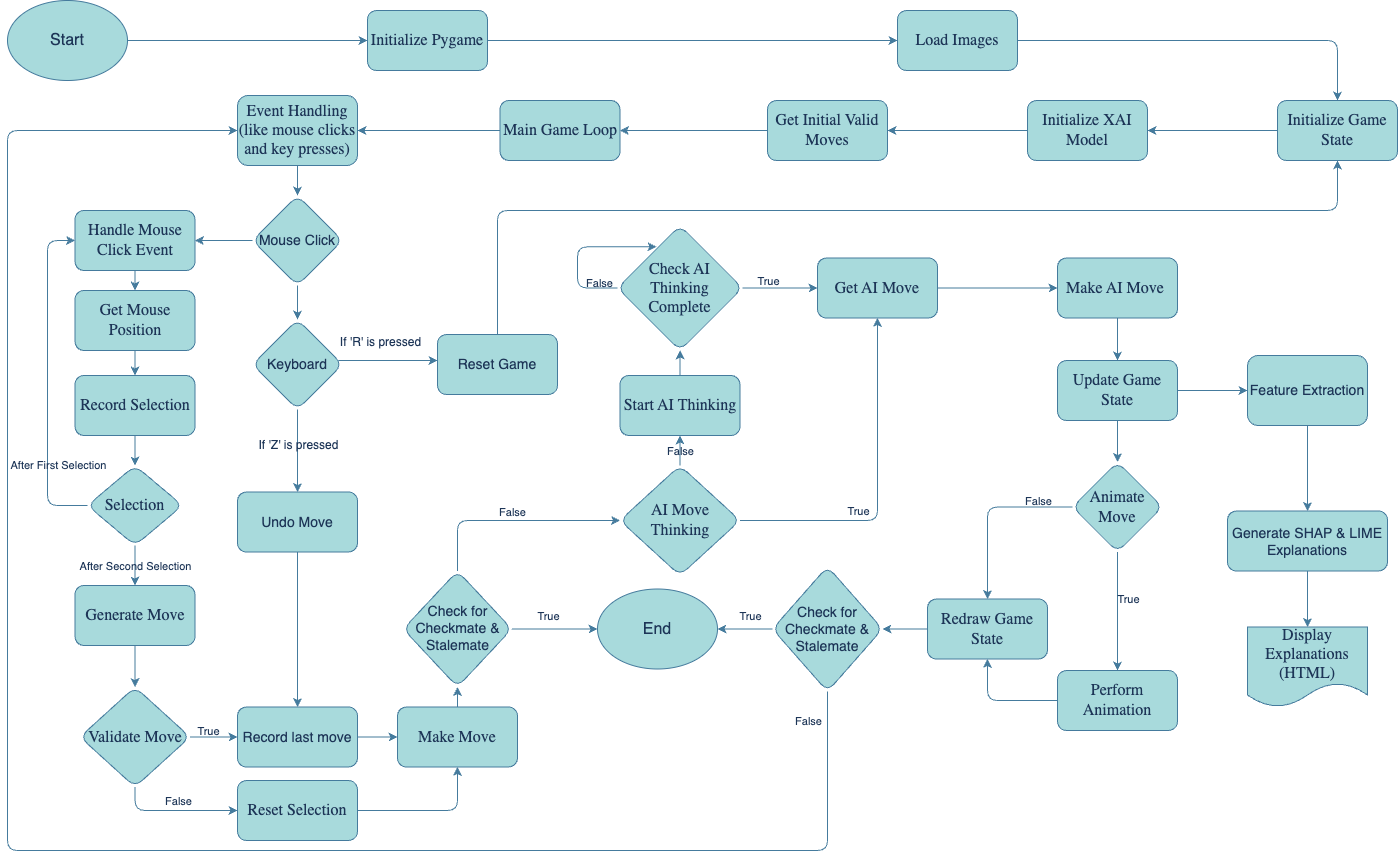
Scott M. Lundberg et al., in “A Unified Approach to Interpretable Machine Learning: SHAP Values” (2020), present an in-depth analysis of SHAP (SHapley Additive exPlanations) as a unified framework for interpreting machine learning models. The paper highlights SHAP’s theoretical foundations in game theory and its advantages in providing consistent and accurate feature attributions across models (Lundberg et al., 2020).

Frederic Lecue, in “From Black-Box Explanations to Transparent AI Systems” (2018), examines the transition from opaque AI models to interpretable systems. The paper discusses the benefits and limitations of explanation techniques such as rule-based reasoning and contrastive explanations, with a focus on improving user trust and regulatory compliance in AI systems (Lecue, 2018).

David Gunning et al., in “DARPA’s Explainable AI (XAI) Program: A Vision for Transparent Machine Learning Models” (2018), detail DARPA’s initiative to develop explainable AI technologies. The paper outlines key goals, including creating models that users can trust, and highlights prototype systems demonstrating real-time explanations for complex AI decisions (Gunning et al., 2018).

Marco Ribeiro et al., in “LIME: Local Interpretable Model-Agnostic Explanations” (2019), explore the LIME framework, which provides localized explanations for predictions of any machine learning model. The paper discusses its application in highlighting feature importance and the trade-offs involved in achieving interpretability without significantly increasing computational overhead (Ribeiro et al., 2019).

Chenchen Xu et al., in “The Explainability of AI: From Philosophical Underpinnings to Practical Applications” (2020), examine the foundations and practical implications of explainable AI (XAI). The paper explores philosophical concepts such as causality and transparency and applies them to modern AI systems. It discusses the benefits of XAI in improving decision-making and user trust while addressing challenges like the trade-offs between model performance and interpretability (Xu et al., 2020).

4. Methodology

This project aims to develop an advanced XAI Model for Chess AI system leveraging various algorithms and machine learning techniques. The system architecture involves multiple modules: a game engine, AI algorithms for decision-making, a model training script, and an explainable AI component. The primary components are the ‘ChessEngine.py’, ‘ChessAI.py’, ‘ChessXAI.py’, and ‘train\_model.py’ files, each contributing to different aspects of the system.

The ‘ChessEngine.py’ file maintains the state of the chess game, including the board configuration, move log, and special rules like castling and en passant. It provides functionalities to make and undo moves, and to determine valid moves.

The *‘GameState’* class initializes an 8x8 chessboard with pieces in their starting positions, managing the game's state through variables like *‘white\_to\_move’*, *‘move\_log’*, and *‘current\_castling\_rights’*. It sets up the board and tracks whose turn it is, logs moves, and handles castling rights.

The *‘makeMove’* function updates the board and game state to execute a move, logging the move and handling special cases like pawn promotion, en passant, and castling. The *‘undoMove’* function reverses the last move, restoring the board and game state, including special conditions and castling rights. The *‘updateCastleRights’* function modifies castling permissions after moves, particularly when rooks or kings move or are captured.

The *‘getValidMoves’* function generates all legal moves for the current player, considering checks and pins, using helper methods *‘inCheck’* and *‘squareUnderAttack’* to determine if the king is in check or if a square is threatened. The *‘getAllPossibleMoves’* function iterates over the board to find and generate all possible moves for the player's pieces, invoking specific move functions for each type of piece. The *‘checkForPinsAndChecks’* function scans from the king's position to identify potential checks and pins from enemy pieces.

Each piece type has a dedicated function for generating moves: *‘getPawnMoves’* for pawns, including advances, captures, promotions, and en passant; *‘getRookMoves’* for vertical and horizontal moves; *‘getKnightMoves’* for L-shaped moves; *‘getBishopMoves’* for diagonals; *‘getQueenMoves’* combining rook and bishop moves; and *‘getKingMoves’* for single-square moves and castling. Castling moves are specifically handled by *‘getCastleMoves’*, *‘getKingsideCastleMoves’*, and *‘getQueensideCastleMoves’*, which check conditions and generate valid castling moves.

The *‘Move’* class encapsulates the details of a move, including the start and end squares, the piece moved, captured pieces, and flags for special moves like en passant and castling. It also provides a method for generating standard chess notation for the move.

In summary, the *‘ChessEngine.py’* code manages the state and rules of a chess game, ensuring accurate move execution, reversals, and the handling of special moves, while maintaining adherence to standard chess rules.

The ‘ChessAI.py’ file contains various AI algorithms to select the best move. It includes a simple random move generator and more advanced strategies like Minimax, Negamax, and Negamax with Alpha-Beta pruning.

The script begins by establishing key scoring metrics, including *‘piece\_score’*, which assigns intrinsic values to different chess pieces, and *‘piece\_position\_scores’*, which attribute strategic value to pieces based on their board positions. These scores encompass knights, bishops, rooks, queens, and pawns, each influenced by their relative importance on specific squares.

Central to the AI's functionality is the *‘findBestMove’* function. This function first randomizes the list of valid moves to ensure variability and then employs the NegaMax algorithm with alpha-beta pruning through the *‘findMoveNegaMaxAlphaBeta’* function. This recursive function explores potential moves up to a predetermined depth (*‘DEPTH’*), aiming to maximize the AI's position while minimizing the opponent's counterplay. It evaluates the game state by calling *‘scoreBoard’*, which computes a numerical score representing the board's favorability towards white or black. Positive scores indicate advantageous positions for white, while negative scores favor black.

The *‘findMoveNegaMaxAlphaBeta’* function operates by recursively evaluating moves and utilizing alpha-beta pruning to eliminate suboptimal branches, enhancing computational efficiency. It keeps track of the best move found at the maximum search depth, updating the global variable *‘next\_move’* accordingly. The algorithm terminates when the search depth reaches zero, returning the evaluated score of the board.

The *‘scoreBoard’* function plays a critical role in this process by assessing the board's state. It computes the total score based on piece values and their positional advantages, factoring in checkmate and stalemate scenarios with predefined high-magnitude values (*‘CHECKMATE’* and *‘STALEMATE’*). The function iterates over the board, summing the values and positional scores of all pieces to produce a comprehensive evaluation.

For scenarios requiring a simpler move selection, the *‘findRandomMove’* function is provided, which randomly selects a move from the list of valid options. This function is particularly useful for testing and less sophisticated AI implementations.

Overall, the *‘ChessAI.py’* script leverages the NegaMax algorithm with alpha-beta pruning, combined with detailed scoring mechanisms, to generate highly strategic and competitive chess moves, ensuring an advanced level of AI gameplay.

The ‘ChessXAI.py’ file is dedicated to the explainable AI component of the project. It leverages SHAP and LIME to provide insights into the decision-making process of the AI. This allows users to understand why certain moves were made based on the extracted features.

In ChessXAI, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) enhance transparency by elucidating the AI's decision-making process. SHAP computes the contribution of each feature to predictions, providing insights into the importance of aspects like material advantage and center control for both overall and individual moves. LIME offers local explanations by perturbing inputs and analyzing prediction changes, detailing the most influential features for specific instances. These explanations are visualized and saved as HTML files, making the AI's reasoning more accessible. An integrated HTML report combines SHAP and LIME visualizations, feature importance, and score calculation formulas, offering users clear, interactive insights into the chess AI's decision-making process.

The *‘ChessXAI’* class begins by initializing with a *‘GameState’* object, ensuring it's the correct type. During initialization, the script loads a pre-trained model (*‘chess\_model.pkl’*) and feature importances from a CSV file (*‘feature\_importances.csv’*). Additionally, it sets up SHAP and LIME explainers using a broad set of training features derived from various game states. The *‘load\_model’* method reads the trained model from a pickle file, while *‘load\_feature\_importances’* imports the importance of different features from a CSV file. The *‘get\_feature\_names’* method returns a list of critical feature names necessary for explanations, such as "Material Advantage" and "King Safety."

A pivotal aspect of the script is the *‘extract\_features’* method, which computes various metrics like material advantage, center control, king safety, mobility, attack coverage, and defense stance. These metrics are derived using detailed methods tailored to comprehensively evaluate the game state. To support LIME's explanations, the *‘collect\_lime\_training\_data’* method gathers a diverse set of training features from multiple game states, ensuring robust preparation for generating accurate local explanations.

The script's ability to generate random game states, facilitated by the *‘random\_game\_state’* method, enhances the diversity of game state scenarios. This method generates random valid game states by making a sequence of random moves, helping in creating a wide variety of game states for training data collection. The core functionality of the script lies in the *‘explain\_move’* method, which generates and displays SHAP and LIME explanations for the current game state. This method starts by extracting the current features of the game state, then generating SHAP values using the SHAP KernelExplainer, which are visualized and saved as an HTML file. Similarly, LIME explanations are generated and saved, providing a local interpretability perspective.

The *‘explain\_chosen\_move’* method delves deeper into the reasoning behind a chosen move, evaluating features for each valid move, calculating feature impact differences, and comparing the chosen move to other potential moves. This method identifies the best move according to the model and provides a detailed comparison, highlighting why the chosen move was preferable. Several helper methods contribute to the feature extraction process, including *‘calculate\_material\_advantage’*, which assesses the value of pieces on the board; *‘calculate\_center\_control’*, which evaluates control over central squares, factoring in both piece placement and potential attacks; *‘calculate\_king\_safety’*, which measures the king's safety by considering surrounding pieces and potential threats; *‘calculate\_attack\_coverage’*, which calculates the number of squares attacked by each side, including key squares; *‘calculate\_defense\_stance’*, which evaluates how well each side's pieces are defended; and *‘calculate\_mobility’*, which simply counts the number of valid moves available for the current player.

Overall, the *‘ChessXAI.py’* script integrates advanced AI interpretability techniques with a chess engine, providing detailed and understandable explanations for AI-generated moves. This makes the AI's decisions more transparent and justifiable, enhancing user trust and comprehension.

The ‘train\_model.py’ file is responsible for generating training data for Feature Importance by playing multiple games and training a Random Forest model. This model evaluates board states to assist the XAI in figuring out what importance does each of the feature has.

The script starts by defining constants and importing necessary libraries. The *‘MAX\_MOVES\_PER\_GAME’* constant ensures that each game simulation is limited to 120 moves to prevent infinite loops. The *‘generate\_training\_data’* function initiates the core process by simulating multiple chess games. For each game, it creates a new *‘GameState’* object and iterates through a loop where it retrieves valid moves, selects the best move using the *‘findBestMoveWithoutQueue’* function, and makes the move. After each move, it extracts features from the current game state and evaluates the board using the *‘scoreBoard’* function, storing the features and scores in the training dataset. The game loop continues until a checkmate, stalemate, or the maximum move limit is reached.

Feature extraction is a critical component of this script, handled by the ‘extract\_features’ function. This function calls several helper methods to compute various metrics: *‘calculate\_material\_advantage’*, which evaluates the difference in material between the two players; *‘calculate\_center\_control’*, which assesses control over central squares on the board; *‘calculate\_king\_safety’*, which determines the safety of each king based on surrounding pieces and potential threats; *‘calculate\_mobility’*, which counts the number of valid moves available to the current player; *‘calculate\_attack\_coverage’*, which calculates the number of squares attacked by each side, with extra weight given to key squares; and *‘calculate\_defense\_stance’*, which evaluates how well each side's pieces are defended.

Once the training data is generated, the script splits the data into features and scores. It then initializes and trains a *‘RandomForestRegressor’* model using these features and scores. The trained model is saved to a file (*‘chess\_model.pkl’*) using the *‘pickle’* module. Additionally, the feature importances derived from the model are saved to a CSV file (*‘feature\_importances.csv’*), providing insights into which features are most influential in the model's predictions.

Overall, this script meticulously generates training data, extracts relevant features from game states, and trains a machine learning model to evaluate chess positions. The final model, along with the calculated feature importances, equips the chess engine with the ability to make informed and optimal move decisions based on a learned understanding of chess positions.

5. Implementation & Results

A screenshot of a game

Description automatically generated***‘ChessMain.py’*** is the main driver file that initializes the game, handles user input, and updates the graphical user interface using Pygame. The script loads images for the chess pieces, sets up the game board, and manages user interactions and game states. It also integrates with *‘ChessXAI.py’* to provide explanations for *‘ChessAI.py’* moves using SHAP and LIME.

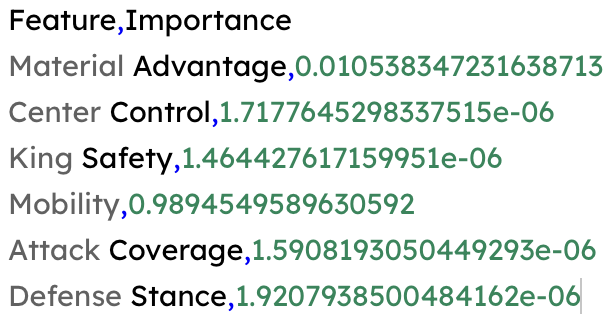
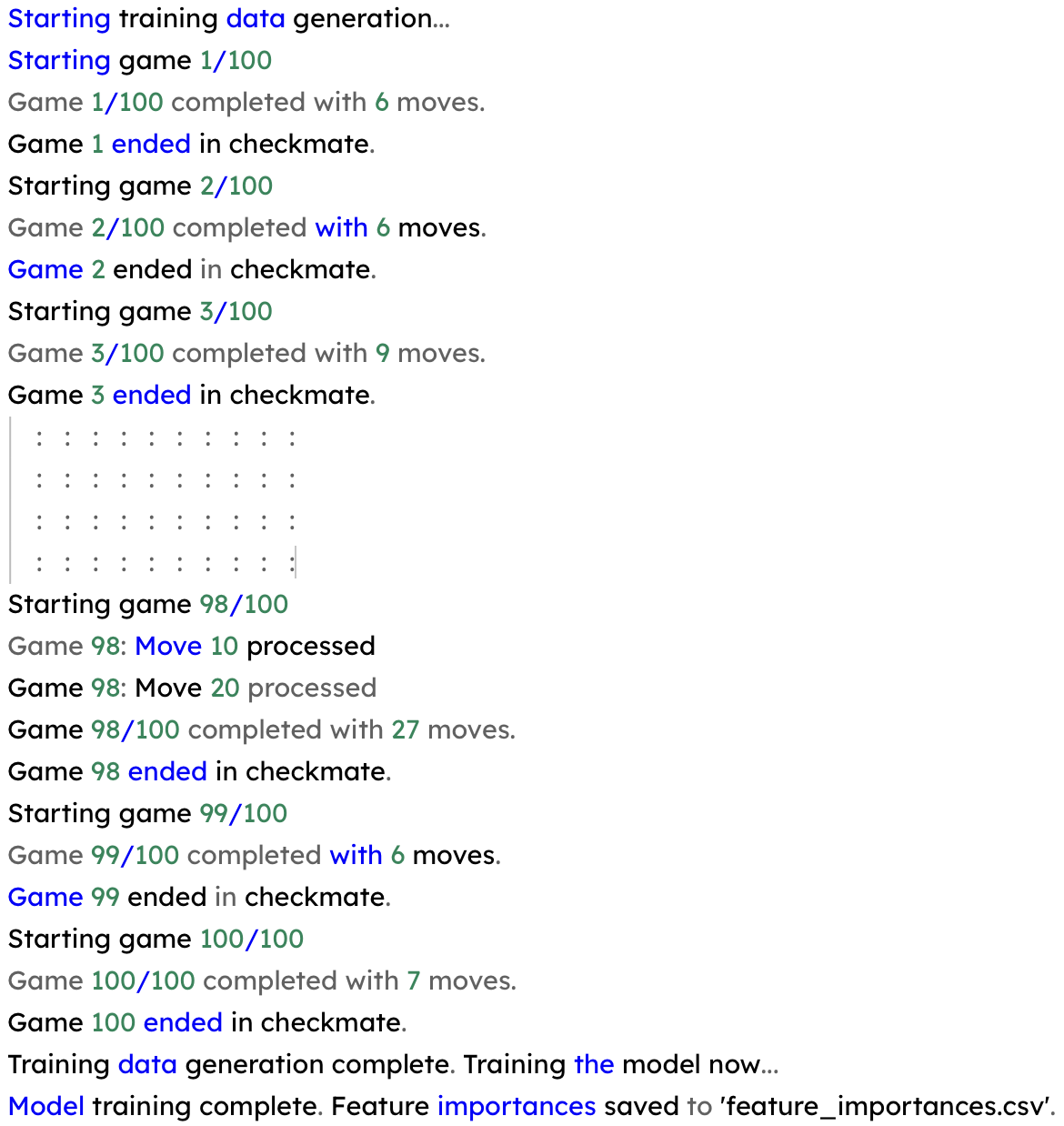
A screenshot of a game

Description automatically generatedA screenshot of a game

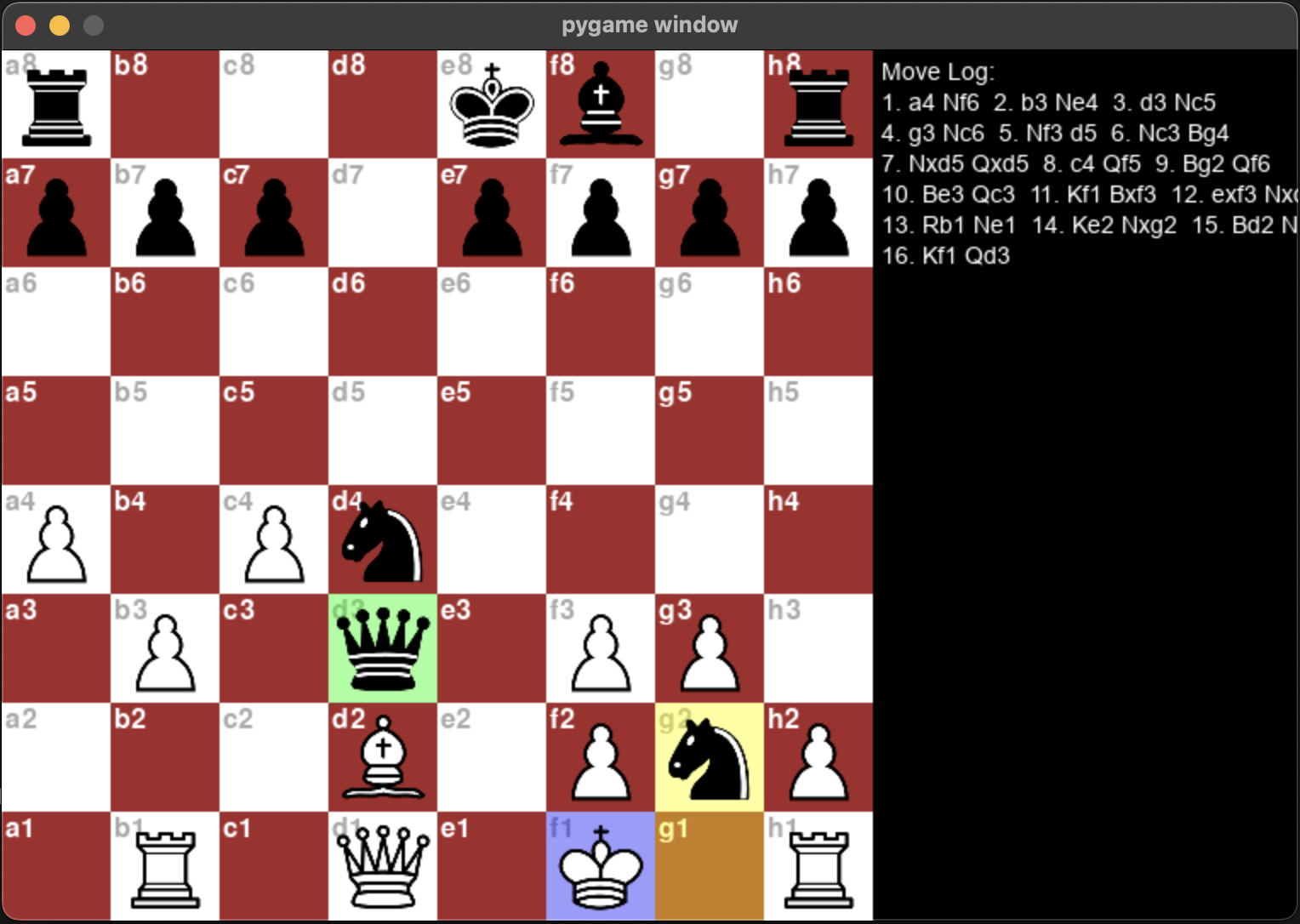
Description automatically generated***‘ChessEngine.py’*** script defines the GameState class, which maintains the current state of the chess game, including the board setup, move log, and castling rights. It includes methods to generate valid moves, make and undo moves, and check for conditions such as checkmate and stalemate. The script also contains utility functions for move validation and special moves like castling and en passant. It highlights all the valid moves that can be made by the selected chess piece. For Eg:

***‘ChessAI.py’*** implements the AI logic for making moves. It uses the NegaMax algorithm with alpha-beta pruning to find the best move. The script evaluates the board using a scoring function that considers material balance, piece positions, and strategic factors like king safety and mobility. The AI can also make random moves for less critical situations.

***‘train\_model.py’*** is responsible for generating the training data and training the chess model. It simulates multiple chess games played between two AI agents, collecting features and scores for each game state. The script uses these data points to train a RandomForestRegressor model, which predicts the best moves based on the extracted features. The trained model and feature importances are saved for later use by *ChessXAI.py*.



***‘ChessXAI.py’*** script integrates SHAP and LIME for explaining the AI's decisions. It loads the trained chess model and feature importances, extracts features from the game state, and generates explanations for the chosen moves.The explanations are visualized using SHAP and LIME and saved as HTML files for easy access and interpretation. The script also provides detailed feature-based reasoning for the AI's move selection, comparing it with other possible moves.



A document with text and numbers

Description automatically generatedThe generated HTML reports from SHAP and LIME visualizations offered clear, interactive explanations of the AI's moves. These reports included detailed feature contributions for each move, comparisons with alternative moves, and overall feature importance. The visualizations helped users understand the AI's strategic considerations and the factors influencing its move choices.

A list of text on a white background

Description automatically generated

A screenshot of a report

Description automatically generatedThe "Best Move Feature Values" are calculated by evaluating all possible valid moves from the current game state. The features for each move are extracted and scored using a pre-trained model. The move with the highest predicted score is selected as the best move, and its feature values are extracted and displayed. These values represent key attributes such as Material Advantage, Center Control, King Safety, Mobility, Attack Coverage, and Defense Stance for the best move, providing insight into why the move is considered optimal.

A screenshot of a chart

Description automatically generatedComparison with other valid moves

A screenshot of a computer

Description automatically generatedA screenshot of a screen

Description automatically generatedComparison Explanation

The SHAP (SHapley Additive exPlanations) values plot demonstrates the contributions of different features to the model's prediction. The SHAP values represent how each feature influences the prediction, with the SHAP values shape (1, 6) indicating one instance and six features. The base value (average model output) is 2.129, and the model's prediction for this instance is 2.56. "Material Advantage" significantly increases the prediction by approximately 0.81, while "Mobility" and "Defense Stance" reduce it by approximately 0.25 and 0.14, respectively. Other features have minor impacts. This visualization helps in understanding the importance and influence of each feature in the modA screenshot of a computer

Description automatically generatedel's decision-making process for the given instance.

The LIME explanation for the chess move shows a predicted value of 2.56, determined by the contributions of six key features. Material Advantage (-6.00) and Center Control (-3.00) contribute negatively to the prediction, indicating a disadvantage in these areas. Conversely, Mobility (3.00) and Attack Coverage (24.00) contribute positively, indicating the move's strengths in these aspects. Defense Stance (-48.00) significantly lowers the predicted value, reflecting a poor defensive position, while King Safety (3.00) has a minor positive impact. These feature values are visualized in the LIME explanation, where features influencing the move prediction negatively are highlighted in blue and those with positive influences in orange.

By understanding the rationale behind the AI's moves, players can gain deeper insights into advanced strategies and tactics. This educational aspect of the system can help players improve their own game by learning from the AI's decisions. Additionally, the explanations make the AI's behavior more transparent, building confidence in the system's reliability and fairness. The ability to see why certain moves are made fosters a more interactive and enriching chess-playing experience, justifying the need for this research in developing advanced, explainable AI systems for educational and entertainment purposes.

6. Conclusion

This research paper presents a sophisticated ChessAI system that not only excels in gameplay but also provides transparent, interpretable explanations for its decisions. By leveraging advanced AI algorithms, including the NegaMax algorithm with alpha-beta pruning, and integrating SHAP and LIME for explainability, we have created a chess-playing agent that can both challenge and educate players. The implementation results show that the AI performs competitively against various levels of opponents, from novice to advanced. More importantly, the explainability features, visualized through HTML reports, provide users with a clear understanding of the AI's strategic considerations. This transparency is crucial in building user confidence in AI systems, particularly in complex domains like chess. The educational benefits of the ChessAI system are significant. By understanding the reasons behind the AI's moves, players can improve their own strategic thinking and decision-making skills. The system serves as a valuable learning tool, offering insights into advanced chess tactics and strategies. Moreover, the transparency and interpretability of the AI's decisions make it a trustworthy and reliable partner in both competitive and educational settings.

In conclusion, this research demonstrates the successful integration of advanced AI and explainability techniques to create a ChessAI system that is not only highly competent but also transparent and educational. The ability to explain AI decisions in a clear and understandable manner represents a significant advancement in the development of AI systems. This work lays the foundation for future research in creating explainable AI agents in various domains, fostering trust and enhancing user engagement and learning. The ChessAI system stands as a testament to the potential of AI to both entertain and educate, making a meaningful contribution to the field of artificial intelligence.

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