

CHEAT DETECTION IN CHESS: ANALYZING PGN FILES

Dissertation Presentation

BITS ID – 2022AC05327

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PRESENTATION OVERVIEW

1. Introduction to Chess Cheating	7. Results & Statistical Analysis
2. Problem Statement & Significance	8. Challenges & Limitations
3. Research Objectives & Contributions	9. Conclusions & Key Findings
4. Literature Review & Current Approaches	10. Future Work & Enhancements
5. Methodology Framework	11. Discussion
6. Implementation Details	12. Q&A



01

INTRO



The image features a dark, reflective surface with several white chess pieces. In the upper center, a knight and a king are standing upright. To their right, a queen is lying on its side. On the far left, a pawn is lying on its side. On the far right, a rook is standing upright. The pieces are reflected on the glossy surface below them.

INTRODUCTION TO CHESS CHEATING

Cheating in chess on online platforms is on a constant rise. There's been an increased prevalence since 2020. Engine assistance: Stockfish, Leela Chess Zero & AlphaZero provide superhuman move accuracy

DETECTION CHALLENGES

- No physical tells in online environments
- Sophisticated methods (togglng between screens, consulting engines selectively)
- Varying skill levels making baseline difficult to establish

Impact on Chess Community: Erosion of trust and competitive integrity

Need for automated detection: Statistical methods to complement human arbitration

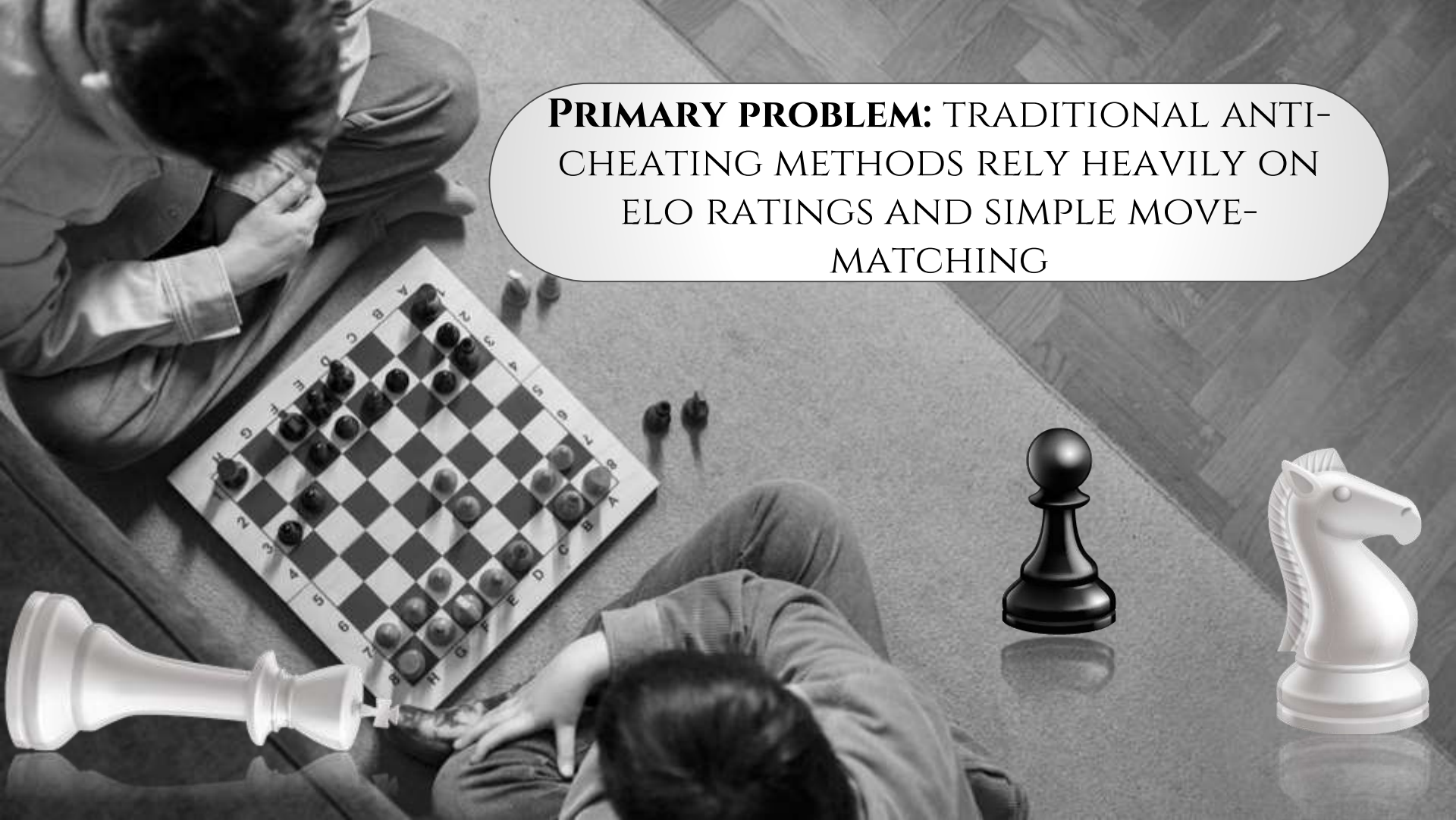


02

PROBLEM STATEMENT



PRIMARY PROBLEM: TRADITIONAL ANTI-CHEATING METHODS RELY HEAVILY ON ELO RATINGS AND SIMPLE MOVE-MATCHING



LIMITATIONS OF CURRENT APPROACHES:

- Proprietary “black box” algos
- High false positive rates
- Difficulty in distinguishing coincidental engine alignment from cheating

Research question: Can PGN analysis identify statistical anomalies indicative of computer assistance?

Significance: Maintaining competitive integrity in online platforms, supportive tournament arbiters with objective evidence, providing transparent detection methods

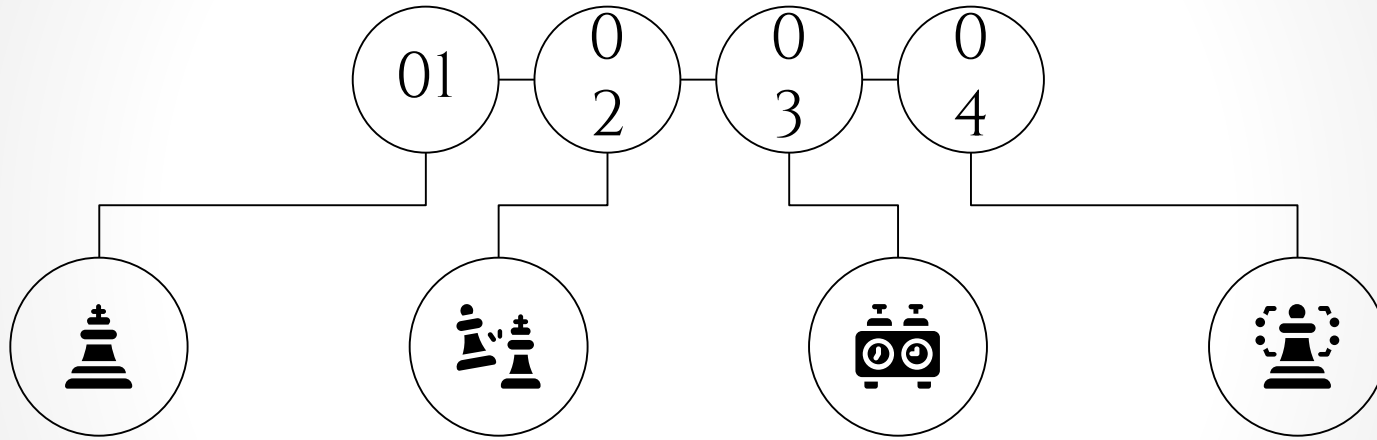


03

RESEARCH
OBJECTIVES &
CONTRIBUTIONS



PRIMARY OBJECTIVES



Develop automated framework for cheat detection using PGN data

Implement CPL metrics to evaluate move precision

Create visualization tools for pattern identification

Build machine learning models to classify suspicious play



NOVEL CONTRIBUTIONS:

- ❑ Integration of multiple detection parameters (not just engine matching)
- ❑ Focus on game-length analysis as a complementary indicator
- ❑ Open-source approach with transparency in methodology
- ❑ Use of modern ML techniques (achieving 95% accuracy with Neural Networks)



WHAT IS CPL (CENTIPAWN LOSS)?

Definition: Numerical measure of move quality relative to optimal engine move

- 100 centipawns = value of one pawn
- Lower CPL = closer to perfect (engine) play

CPL Characteristics:

- Grandmasters: ~15–20 average CPL
- Club players: ~50–100 average CPL
- Beginners: ~150+ average CPL

Detection Relevance:

- Unnaturally consistent low CPL across games suggests engine assistance
- Important to consider game complexity, time controls, and position criticality
- Pattern of CPL more revealing than absolute values



04

LITERATURE
REVIEW



LITERATURE REVIEW

- **Historical Development:**

- Early statistical approaches (Regan & Haworth, 2011)
- Chess.com's proprietary system development (2014–present)
- Lichess's IRWIN detector (2017)

- **Current Detection Methods:**

- Z-score analysis of move matching percentages
- Time usage patterns and correlation with move difficulty
- Move consistency across different game phases
- Player performance deviation from historical results

- **Research Gaps:**

- Limited transparency in commercial implementations
- Inadequate contextual move analysis
- Challenges in real-time monitoring and intervention
- Scarcity of labeled datasets for supervised learning

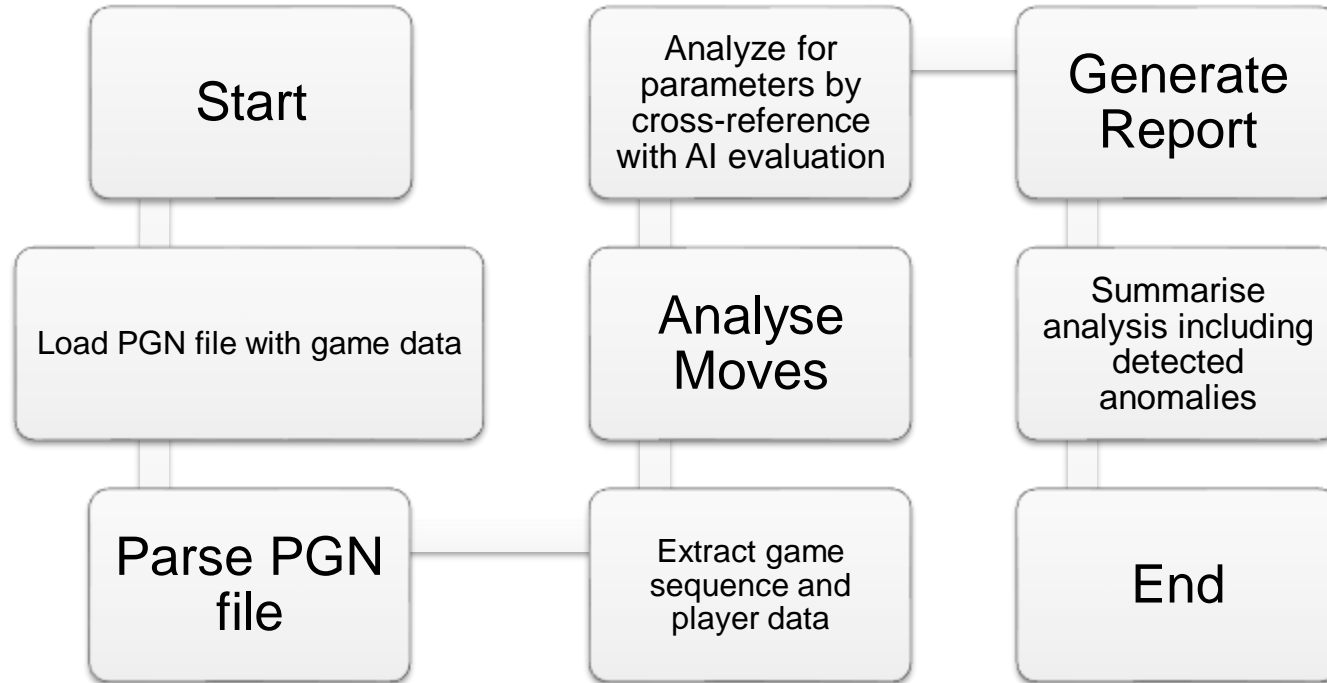


05

METHODOLOGY FRAMEWORK



PGN Analysis Methodology



PROCESS FLOW

01

GAME DATA

Extract game data and
player information



02

COMPUTE

Compute move-by-
move engine metrics



03

CPL

Apply CPL and other
metrics



04

ANALYSIS

Generate
comprehensive analysis
report



06

IMPLEMENTATION



IMPLEMENTATION

Dataset Composition:

- PGN files from Chess.com and Lichess
- Range of Elo ratings (800–2500)
- Mix of known fair games and confirmed cheating cases
- Various time controls (bullet, blitz, rapid, classical)

Technology Stack:

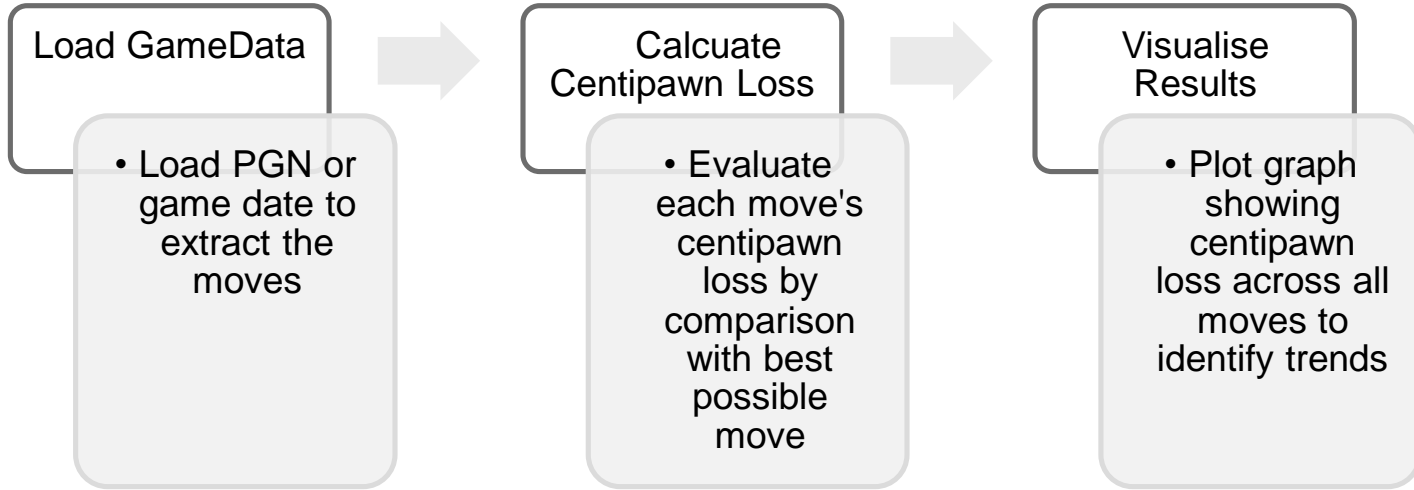
- Python with chess.pgn library for parsing
- Stockfish 16 for engine analysis (depth 20)
- Pandas for data manipulation
- Matplotlib and Seaborn for visualization
- Scikit-learn and TensorFlow for ML models

Implementation Challenges:

- Handling large PGN files efficiently
- Optimizing engine analysis time
- Accounting for different time controls in evaluation



Centipawn Loss Across Moves



CENTIPAWN LOSS CALCULATION PROCESS

Implementation Details:

- Extraction of move sequences in UCI format
- Engine evaluation at consistent depth (depth 20)
- Calculation formula: $CPL = \max(0, \text{evaluation_before_move} - \text{evaluation_after_opponent_best_response})$
- Exclusion of book moves (first 10 moves) to reduce noise
- Special handling for forced moves and time trouble positions



MACHINE LEARNING MODEL PERFORMANCE

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	85%	88%	83%	85%
Random Forest	92%	90%	93%	91%
Neural Network	95%	94%	96%	95%



Feature Engineering:

- Average CPL across game phases
- CPL variance and standard deviation
- Move matching percentage with top engine choices
- Time usage patterns and correlation with move complexity
- Game length relative to player rating

Model Selection Rationale:

- Neural Network provides best overall performance
- Random Forest offers good interpretability with strong results
- Decision Tree serves as baseline and provides explainable rules

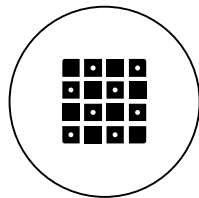


07

RESULTS & ANALYSIS

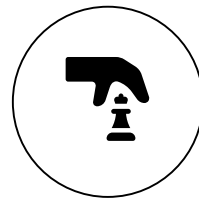


RESULTS: IDENTIFYING SUSPICIOUS PATTERNS



PRIMARY INDICATORS

- Consistently low CPL across complex positions
- Unnatural CPL stability
- High alignment with top engine choices in critical positions
- Incongruence between move strength and player rating



SECONDARY INDICATORS

- Unusual game length patterns
- Inconsistent time usage (very quick complex moves)
- Performance spikes in specific tournaments or time periods
- Drastic improvement without corresponding rating increase



CLASSIFICATION THRESHOLDS



LOW CONFIDENCE

Only secondary indicators
present



MEDIUM CONFIDENCE

One primary + multiple
secondary indicators

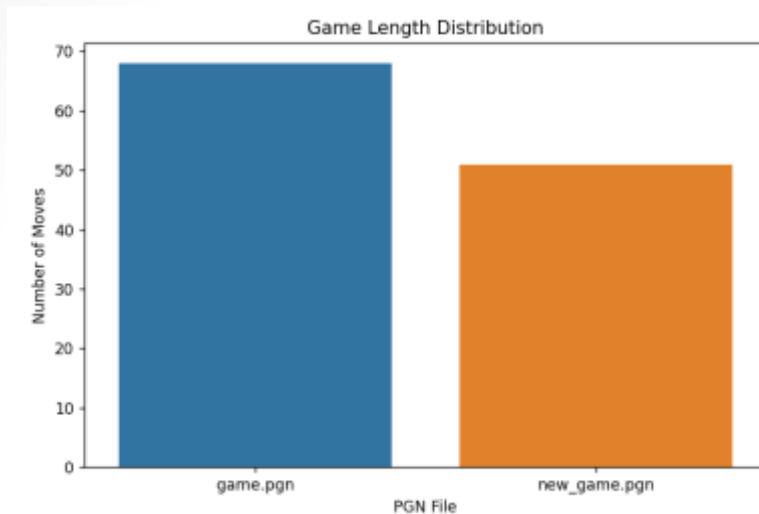


HIGH CONFIDENCE

Multiple primary
indicators present



GAME LENGTH DISTRIBUTION ANALYSIS

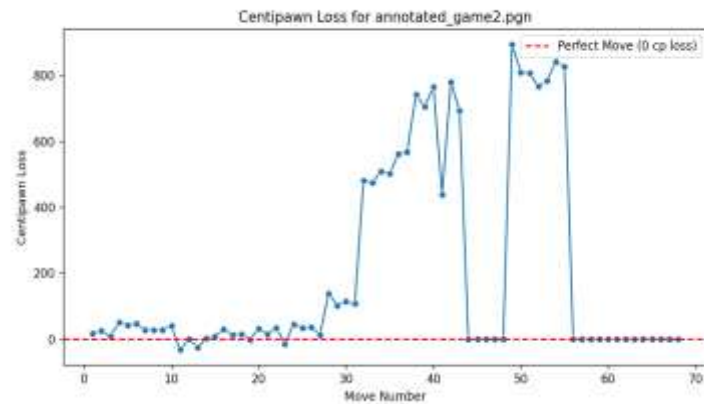
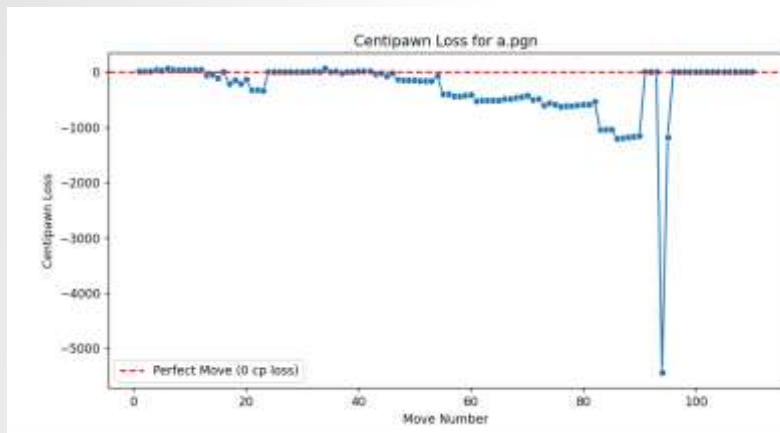


Analytical Insights:

- Normal distribution centered around 40 moves for fair play
- Bimodal distribution for suspicious accounts:
 - Very short games (quick wins with engine assistance)
 - Very long games (prolonged optimal defense)
- Correlation between game length and outcome for suspected cheaters
- Time control influence on distribution patterns



CPL TREND ANALYSIS



Pattern Interpretation:

- Figure 1: Typical human player showing variable CPL with occasional spikes
- Figure 2: Suspected engine assistance showing unnaturally flat, low CPL

Key Observations:

- Critical position identification (where decisions are complex)
- Move timing correlation with CPL (suspiciously quick perfect moves)
- Consistency across multiple games from same player
- Phase-specific analysis (opening, middlegame, endgame)



08

CHALLENGES & LIMITATIONS



TECHNICAL CHALLENGES (TC) & METHODOLOGICAL LIMITATIONS (ML)

01

TC: Computational
intensity of engine
analysis

02

TC: Handling different
chess engine
versions/depths

03

TC: Accommodating
various time controls in
analysis

04

ML: Reliance on
annotated PGN files for
training data

05

ML: False positives with
very strong human
players

06

ML: Intentional
suboptimal play to avoid
detection



ETHICAL CONSIDERATIONS



FALSE ACCUSATION

Balancing detection with
false accusation risk



TRANSPARENCY

Transparency in methodology
to ensure fairness



PRIVACY

Privacy concerns with
player data analysis



09

CONCLUSIONS & KEY FINDINGS



Primary Conclusions



CPL analysis
effectively
differentiates fair
from engine-
assisted play



Game context
(complexity, phase,
time control) crucial
for accurate
detection



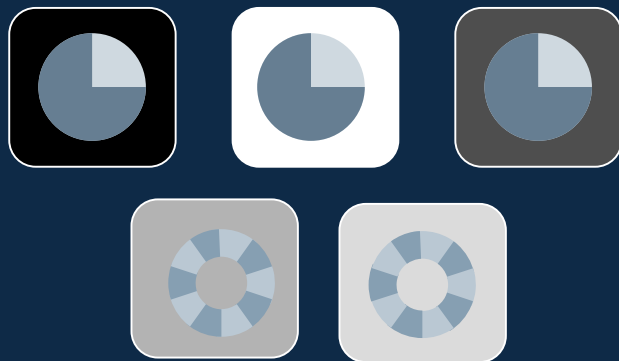
Multi-factorial
approach
reduces false
positives



Neural Network
models achieve
95% accuracy in
classification

Key Findings

- Pattern consistency more revealing than individual move accuracy
- Game length distribution provides valuable supplementary evidence
- Time usage patterns strongly correlate with suspicious play
- Combined metrics approach outperforms single-factor detection



PRACTICAL APPLICATIONS

TOURNAMENTS

Tournament screening
tool for arbiters



55%

CHESS SITES

Platform-level
implementation for
online chess sites



45%



Educational resource for fair play enforcement



10

FUTURE WORK



TECHNICAL ENHANCEMENTS

- Real-time analysis capability for tournament monitoring
- Cloud-based implementation for scalability
- Mobile application for arbiters and tournament directors
- Integration with chess platform APIs



Improvements and Research Extensions



Methodological Improvements:

- Expanded training dataset with more confirmed cases
- Advanced neural network architectures (LSTM, Transformer)
- Incorporation of psychological factors and playing style
- Adaptive thresholds based on time control and player rating

Research Extensions:

- Application to other strategic games (Go, Shogi)
- Self-improving detection through continuous learning
- Combined hardware/software solutions for tournament play

ACKNOWLEDGEMENTS

SUPERVISION AND GUIDANCE

- Milin Shah, Bank of America (Primary Supervisor)
- BITS Pilani Department of AI & ML Faculty

TECHNICAL SUPPORT

- Stockfish Development Team
- Python-chess Library Contributors

DATA SOURCES

- Chess.com Research Dataset
- Lichess Open Database

RESEARCH ASSISTANCE

- Chess Community Forum Contributors
- Fellow BITS Pilani Students & Researchers



CHESS COMMUNITY FRIENDS



- Manan Pahwa, Purdue University (EECS), Indiana, USA
 - i. PGN dataset contributions (chess.com) for test cases and sample games
 - ii. Providing expert perspectives on human play patterns
 - iii. Invaluable feedback on early detection algorithms
 - iv. Dissertation idea incubator
 - v. Chess coach
- Moin Memon, Bank of America, GBS Chess Championship Winner 2022
 - i. Assistance with testing across various skill levels
 - ii. Local chess club member participant for controlled testing
 - iii. Tournament coordinator sharing insights on practical implementation needs



ACKNOWLEDGEMENTS CONTINUED



11 & 12

DISCUSSION + Q&A



PANEL MEMBERS

Any feedback and questions for me?





THANK YOU

Any questions? Please reach out to me –

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