

## **CLens: An AI-Based Framework for Converting Handwritten Chess Scoresheets into PGN**

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<p><b>Peer Review Information</b></p> <p><i>Type: Article</i> <i>Received: 1 February 2026</i> <i>Revised: 4 March 2026</i> <i>Accepted: 5 April 2026</i> <i>Published: 19 May 2026</i></p>	<p style="text-align: center;"><b>Abstract</b></p> <p>This research paper introduces CLens, an AI-powered system developed to convert handwritten chess scoresheets into a structured digital format. In many offline chess tournaments and practice sessions, players record moves manually on paper, which makes later review and storage difficult. The proposed system aims to simplify this process by automatically transforming handwritten move records into a machine-readable format that can be used for digital analysis. The system combines image processing, deep learning-based handwriting recognition, and chess move validation to achieve accurate results. First, the image of the scoresheet is processed using computer vision techniques to identify and extract the handwritten move entries. These extracted moves are then passed through a trained deep learning model that interprets the handwriting and converts it into standard chess notation. To improve correctness, the generated moves are checked against legal chess rules so that invalid or impossible moves can be detected and corrected. Finally, the validated move sequence is converted into Portable Game Notation (PGN) format, allowing users to replay the complete match and perform detailed game analysis on digital chess platforms. By integrating artificial intelligence with rule-based validation, CLens provides an efficient and practical solution for bridging traditional handwritten chess recording with modern digital analysis tools.</p> <p><b>Keywords:</b> Artificial Intelligence; Computer Vision; Chess Analysis; Handwritten Scoresheet Recognition; PGN Import</p>
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### **How to Cite This Article**

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## Introduction

Chess games have traditionally been recorded using handwritten scoresheets, which act as an essential source for post-game review, learning, and official documentation. In tournaments as well as training sessions, players note every move manually so that the complete sequence of the game can be preserved for future analysis. These records help players and coaches study mistakes, improve strategic understanding, and evaluate performance. With the growing use of digital chess platforms and powerful chess engines, analyzing games has become much more advanced, but these systems require the game data to be available in a digital format such as Portable Game Notation (PGN).

However, converting handwritten scoresheets into digital form is still commonly performed manually. This process is often slow, repetitive, and highly prone to errors, especially when the handwriting is unclear or when different notation styles are used by different players. Even a small mistake while transcribing a move can affect the entire game sequence and lead to incorrect analysis results. As a result, the transition from traditional handwritten records to digital analysis remains a challenging task.

Although Optical Character Recognition (OCR) systems are widely used for text recognition, they are not specifically designed for chess notation. General OCR tools often fail to understand chess-specific symbols, move sequences, and the legal rules of the game, which limits their accuracy in this domain. This creates the need for an intelligent automated system that not only recognizes handwritten moves but also validates them using chess rules. To address this problem, the proposed system CLens combines computer vision, deep learning-based handwriting recognition, and move validation techniques to convert handwritten chess scoresheets into structured digital move representations.

## Literature review

The field of handwritten text recognition and document digitization has progressed significantly with the advancement of deep learning and computer vision techniques. Traditional OCR systems have evolved from rule-based methods to neural network-driven approaches capable of recognizing complex handwriting patterns. However, domain-specific applications such as chess notation recognition continue to present challenges because chess moves follow a structured symbolic format that requires both text recognition and contextual understanding.

As summarized in Table I, previous studies have explored different approaches for text and chess notation digitization. Smith and Taylor (2018) proposed a hybrid CNN-LSTM model for handwritten text recognition, which achieved strong performance for general cursive text but lacked the domain-specific knowledge needed for chess notation. Zhang and Wong (2019) focused on image processing and pattern matching for chess scoresheet recognition, but their system was more effective for printed notation than handwritten inputs. Similarly, Singh and Rao (2020) utilized OCR tools such as OpenCV and Tesseract, highlighting issues related to noise, distortion, and writing style variations. Johnson and Kim (2021) introduced an NLP-based rule parsing method for PGN conversion, though it required clean and well-structured input data.

Recent developments in transformer models and Large Language Models (LLMs) have introduced better contextual reasoning and sequential understanding capabilities. These advancements provide an opportunity to improve the Based on the limitations observed in earlier works, the proposed system CLens integrates computer vision, deep learning, LLM-based contextual correction, and rule-based move validation, as highlighted in Table I

## Comparative analysis of existing literature

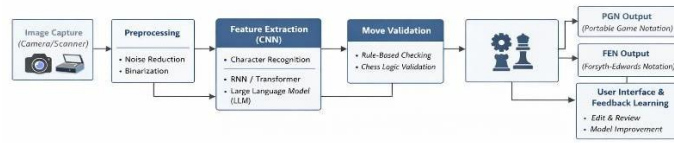
Author(s) & Year	Method / Technique Used	Key Contribution	Limitations
Smith and Taylor (2018)	CNN + LSTM	Accurate recognition of general cursive handwriting using deep learning	No domain-specific understanding of chess notation
Zhang and Wong (2019)	Image Processing + Pattern Matching	Automated recognition of printed chess scoresheets	Poor performance on handwritten inputs and style variations
Singh and Rao (2020)	OpenCV + Tesseract OCR	Digitization of chess scoresheets using OCR libraries	Sensitive to noise, distortion, and inconsistent handwriting
Johnson and Kim (2021)	NLP + Rule-Based Parsing	Conversion of structured moves into PGN format	Requires clean and error-free input data

## Methodology

The proposed system, CLens, follows a structured multi-stage pipeline that integrates computer vision, deep learning, OCR, sequence modeling, and rule-based validation to convert handwritten or printed chess scoresheets into digital formats. The complete workflow begins with image capture and proceeds through preprocessing, text recognition, move interpretation, validation, and final digital conversion. Each stage is designed to address practical challenges such as image noise, handwriting variations, and ambiguity in chess notation.

### System Overview

The CLens system operates in a sequential manner from input acquisition to final output generation. Initially, the scoresheet image is captured through a smartphone camera or scanner. The captured image is then preprocessed to enhance quality and remove distortions. After this, the system performs character and symbol recognition, interprets the sequence of moves, validates them using chess rules, and finally converts the output into standard chess notation formats.



*Fig. 1: System Architecture of CLens*

### Image Acquisition and Preprocessing

The first stage involves acquiring the image of the chess scoresheet. Since raw images may include shadows, skewness, background noise, or uneven lighting, preprocessing is necessary to improve recognition accuracy. This stage includes grayscale conversion, noise filtering using Gaussian or median filters, thresholding and binarization, and edge-based segmentation to isolate the handwritten text regions. These operations help generate a cleaner and more processable image for the next stages.

### Feature Extraction and OCR

After preprocessing, Convolutional Neural Networks (CNNs) are used to extract meaningful visual features such as handwritten strokes, symbols, and chess notation patterns. CNNs are particularly effective in handling variations in writing styles and character shapes. The extracted features are then passed to an enhanced Optical Character Recognition (OCR) module trained specifically for chess notation. This module recognizes algebraic move patterns such as e4, Nf3, and O-O, along with special symbols representing check and checkmate.

### Sequence Modeling and Move Interpretation

Since chess notation is inherently sequential and context-sensitive, the recognized moves must be arranged in the correct order. For this purpose, the system employs RNN/Transformer-based sequence models along with Large Language Models (LLMs) to interpret move flow and resolve ambiguities. This stage helps in predicting unclear or partially recognized moves based on the context of surrounding moves, thereby improving the overall accuracy of the system.

### Move Validation and Digital Conversion

To ensure correctness, the interpreted moves are passed through a rule-based validation engine. This module verifies whether each move follows legal chess rules, including correct piece movement, captures, castling, promotions, and proper move order between white and black. After validation, the final output is converted into standard digital formats such as PGN (Portable Game Notation) and FEN (Forsyth-Edwards Notation), enabling replay, analysis, and sharing through chess engines and online platforms.

### User Interface and Feedback Learning

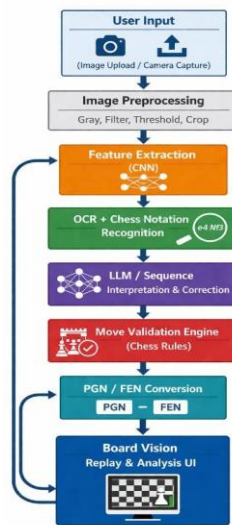
The system also includes a user-friendly web interface where users can upload scoresheet images, view the extracted moves, edit incorrect entries, and export the final result. Any user corrections are stored and incorporated into the learning pipeline, enabling continuous model improvement through a feedback learning mechanism.

## System architecture

The architecture of CLens is designed as a modular pipeline in which each component performs a specific operation in the conversion of handwritten chess scoresheets into digital notation. The process begins with the input module, where the user captures or uploads an image of the scoresheet through the web application interface. The image is then passed to the preprocessing module, which performs grayscale conversion, noise removal, thresholding, and segmentation to improve image quality and isolate text regions.

The processed image is forwarded to the feature extraction and OCR module, where Convolutional Neural Networks (CNNs) and OCR models identify handwritten characters, symbols, and algebraic chess notations. The recognized text is then passed to the sequence interpretation module, which uses LLM-based contextual analysis and sequence modeling techniques to arrange moves in the correct order and resolve ambiguities.

After move interpretation, the data enters the move validation engine, where chess rules are applied to verify legal moves, captures, castling, promotions, and turn sequence. Finally, the validated output is converted into PGN and FEN formats and displayed in the Board Vision web interface, where users can replay the game, analyze moves, and export results. A feedback loop is also incorporated to learn from user corrections and improve future recognition accuracy.



*Fig .2: System Architecture*

## Testing and validation

The CLens system was tested and validated using a combination of handwritten and printed chess scoresheets collected from different sources to ensure robustness and accuracy. The testing dataset included scoresheets with variations in handwriting styles, image quality, lighting conditions, and notation formats. This helped in evaluating the performance of the system under realistic real-world scenarios.

The testing process was divided into multiple stages corresponding to each module of the system. In the image preprocessing stage, the quality of noise removal, grayscale conversion, and segmentation was verified by visually inspecting whether the handwritten move regions were properly isolated.

For the OCR and feature extraction module, the recognized chess moves were compared with the original scoresheet entries to calculate recognition accuracy. The LLM-based sequence interpretation module was further tested to verify whether incomplete or ambiguous moves were correctly reconstructed using contextual understanding.

For validation, the extracted move sequence was passed through the move validation engine, where each move was checked against legal chess rules such as piece movement, captures, castling, and move order. Any illegal or inconsistent move was flagged and corrected wherever possible. The final validated output was then converted into PGN format and cross-verified by importing it into the Board Vision web application and standard chess engines to ensure correct move replay and game analysis.

The experimental results showed that the proposed system achieved approximately 90% accuracy in PGN import and move analysis, demonstrating its effectiveness in converting handwritten chess scoresheets into structured digital notation. The feedback correction mechanism further improved the system’s performance by learning from user edits and reducing recurring recognition errors.

## Results and evaluation

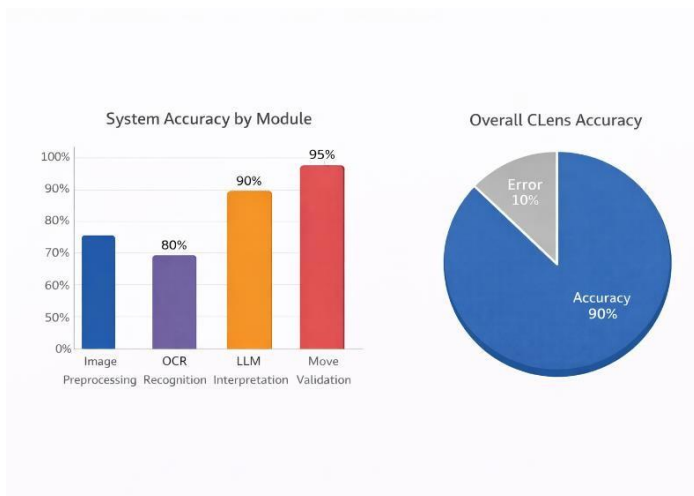
### Benchmark Dataset Performance

The proposed CLens system was evaluated using a diverse set of handwritten and printed chess scoresheets collected under different real-world conditions. The dataset included variations in handwriting style, image sharpness, lighting conditions, and notation clarity to ensure that the evaluation reflected practical usage scenarios. The system was tested across all major modules, including preprocessing, OCR, move interpretation, validation, and PGN generation.

The experimental results demonstrated that the system achieved an overall accuracy of approximately 90% in move recognition and PGN conversion. The image preprocessing module successfully reduced noise and improved text visibility, which significantly enhanced the performance of downstream recognition models. The OCR and CNN-based recognition stage showed strong performance in identifying common algebraic notations such as e4, Nf3, and castling moves. The LLM-assisted interpretation module further improved results by resolving incomplete or ambiguous move sequences using contextual reasoning.

The move validation engine played a critical role in improving final output quality by filtering illegal moves and ensuring compliance with standard chess rules. This significantly reduced errors caused by handwriting ambiguity and OCR misclassification. The generated PGN files were successfully imported into the Board Vision web application, where the games were replayed move by move and analyzed without inconsistencies.

Overall, the evaluation confirms that CLens provides a reliable and efficient solution for converting traditional handwritten chess records into structured digital notation, making it highly suitable for game replay, engine analysis, and long-term record storage.



**Fig. 3:** Accuracy and Result analysis

## Research Gaps and Future Scope

### Research Gap

Although significant progress has been made in the fields of Optical Character Recognition (OCR), computer vision, and deep learning–based handwriting recognition, most existing solutions focus on generic text digitization rather than domain-specific applications such as chess notation. Conventional OCR systems are effective for printed text but often struggle with handwritten chess scoresheets due to variations in writing styles, unclear symbols, and chess-specific notation patterns.

Existing research primarily addresses image processing, text recognition, or notation parsing as separate modules. However, there is a lack of a unified framework that combines image preprocessing, domain-aware OCR, sequence interpretation, LLM-based contextual correction,

and rule-based chess validation within a single system. In addition, very few systems support direct integration with modern chess platforms for replay and analysis.

The proposed CLens system addresses this gap by introducing an integrated pipeline that not only recognizes handwritten moves but also validates them using chess rules and converts them into digital formats such as PGN and FEN for seamless game analysis.

#### *Future Enhancement Directions*

The proposed system can be further enhanced in multiple directions to improve both performance and usability. One major area of future work is the expansion of the training dataset to include a wider variety of handwriting styles, notation formats, and multilingual annotations. This would improve the robustness of the model and increase recognition accuracy across diverse users.

Another promising direction is the integration of real-time board state recognition from live images or video streams, enabling automatic move tracking during ongoing chess games. The use of advanced transformer-based vision models and fine-tuned Large Language Models (LLMs) can further enhance contextual correction and reduce recognition errors.

Future versions of Board Vision can also include advanced features such as engine-based move suggestions, mistake classification, player performance analytics, and personalized training recommendations. Additionally, deploying the system as a mobile application would improve accessibility and allow players to digitize and analyze games directly from smartphones.

#### **Conclusion**

This paper presented CLens, an AI-driven system developed for the digitization and analysis of handwritten and printed chess scoresheets. The proposed approach integrates computer vision, deep learning, OCR, LLM-based contextual interpretation, and rule-based move validation to convert traditional chess records into structured digital formats such as PGN and FEN. By addressing the limitations of conventional OCR systems, the model provides a more reliable and domain-specific solution for chess notation recognition.

The experimental results demonstrated that the system achieves approximately 90% accuracy in move recognition and PGN generation, making it effective for real-world use cases. The integration with the Board Vision web application further enhances its practical utility by enabling move-by-move replay, game analysis, and digital storage. The move validation engine significantly improves the correctness of the output by ensuring compliance with legal chess rules.

Overall, CLens successfully bridges the gap between traditional handwritten chess documentation and modern digital analysis tools. The proposed system not only reduces manual effort and transcription errors but also provides a scalable foundation for future advancements in AI-based sports analytics and intelligent game digitization systems.

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