OCR Sudoku Puzzle Solver: An AI-Powered Approach to Automated Puzzle Solving

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***Abstract*— Sudoku puzzles are popular logic-based number placement games that require systematic problem-solving skills. Traditional manual solving methods are time-consuming, and verifying solutions can be error-prone. This paper presents an AI-based OCR Sudoku Puzzle Solver that automates the detection, recognition, and solving of Sudoku puzzles from image inputs. The system leverages computer vision techniques for grid detection, Optical Character Recognition (OCR) using Convolutional Neural Networks (CNN) for digit recognition, and a recursive backtracking algorithm for puzzle solving. The proposed model is trained on the MNIST dataset for digit classification and utilizes OpenCV for image preprocessing. The results demonstrate high accuracy in digit recognition and successful real-time puzzle solving. The system can be deployed for various use cases, including mobile applications and web-based Sudoku solvers.**

***Index Terms*— Optical Character Recognition, Deep Learning, Convolutional Neural Networks, Sudoku Solving, Computer Vision, AI-Based Image Processing.**

I. INTRODUCTION (*HEADING 1*)

Sudoku is a widely recognized puzzle game that requires players to fill a 9×9 grid such that every row, column, and subgrid contains unique digits from 1 to 9. Manual solving of Sudoku can be time-intensive, and verifying large sets of puzzles manually is impractical. Automating the Sudoku solving process requires advanced techniques in image processing, pattern recognition, and AI-driven decision-making.

This study proposes a deep learning and computer vision-based approach for automating Sudoku puzzle solving from image inputs. The system is designed to extract the Sudoku grid, recognize the digits using OCR, and solve the puzzle using an efficient backtracking algorithm. The primary objectives include:

- Using OpenCV-based image processing to locate and extract the Sudoku grid.
- Employing a trained CNN model to recognize handwritten or printed digits.
- Implementing a backtracking algorithm to generate a valid Sudoku solution.
- Displaying the solved puzzle by superimposing the output onto the original image.

This paper details the implementation, model architecture, and performance evaluation of the OCR Sudoku Puzzle Solver.

II. BACKGROUND AND RELATED WORK

Several studies have explored AI-driven Sudoku solvers. Dugar et al. [1] proposed an augmented reality Sudoku solver using CNNs for digit recognition. Jain et al. [2] introduced a Tree Strength-Infused Enriched Random Forest model for OCR enhancement. Ahmareen et al. [3] implemented a CNN-based handwritten digit recognizer using the MNIST dataset, achieving high classification accuracy. While these methods improve digit recognition, our study integrates AI-powered grid detection, CNN-based OCR, and an optimized backtracking algorithm for end-to-end Sudoku solving.

Traditional Sudoku solvers have relied on rule-based algorithms for solving predefined grids without OCR capabilities. These methods are efficient when the puzzle is available in digital format but fail when working with images of printed or handwritten puzzles. To bridge this gap, recent advancements in deep learning and computer vision have been leveraged to extract and interpret Sudoku puzzles from images. Huang et al. [4] designed a hybrid model combining CNN and Recurrent Neural Networks (RNN) to improve OCR accuracy for noisy handwritten Sudoku puzzles. Similarly, Patel et al. [5] explored an end-to-end pipeline integrating edge detection and deep neural networks to extract and classify digits from Sudoku puzzles with varying fonts and backgrounds. These methods enhanced digit recognition accuracy but lacked an optimized solving mechanism, often leading to incomplete or incorrect solutions.

Other studies [6]-[20] have focused on enhancing Sudoku OCR accuracy, including improvements in feature extraction methods, deep learning architectures, and noise reduction techniques. Kumar et al. [6] developed a CNN-based OCR system specifically trained on noisy Sudoku images, while Lee et al. [7] introduced a graph-based Sudoku solving approach integrated with an OCR pipeline. Singh et al. [8] proposed a hybrid deep learning model for OCR-based Sudoku solving with improved digit segmentation, and Wang et al. [9] investigated transfer learning techniques for improving Sudoku digit classification. Additionally, Chen et al. [10] explored reinforcement learning strategies for dynamically adjusting Sudoku solving strategies, whereas Zhang et al. [11] designed an ensemble CNN model to boost OCR performance in low-resolution Sudoku images.

Several other approaches have focused on improving Sudoku grid extraction and OCR robustness. Miller et al. [12] integrated edge detection methods with CNNs to enhance Sudoku grid extraction, while Garcia et al. [13] proposed an adversarial training mechanism to improve OCR resilience to distorted Sudoku images. Park et al. [14] used a Generative Adversarial Network (GAN) to generate synthetic Sudoku datasets for robust OCR training, and Liu et al. [15] applied multi-stage CNN pipelines for better character segmentation in Sudoku OCR. Mobile and real-time applications have also been explored; Santos et al. [16] introduced a mobile application integrating real-time Sudoku solving with OCR, and Brown et al. [17] developed an interpretable deep learning model for Sudoku OCR with explainability features.

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Further research has examined architectural optimizations and training methodologies for Sudoku OCR models. Nakamura et al. [18] studied the effects of different activation functions on Sudoku OCR model performance, while O'Connor et al. [19] analyzed the impact of dataset augmentation techniques on Sudoku OCR accuracy. Rodriguez et al. [20] presented a cloud-based OCR Sudoku solver using federated learning approaches, highlighting the potential of distributed training methodologies in improving Sudoku OCR capabilities.

Our work builds upon these contributions by integrating robust OCR with an intelligent backtracking solver, ensuring that extracted Sudoku puzzles are solved efficiently. The integration of OpenCV for preprocessing, CNN for classification, and backtracking for solution generation provides a holistic approach to Sudoku automation.

III. METHODOLOGY

A. *Dataset Description*

The digit recognition model is trained using the MNIST dataset, which consists of 60,000 training images and 10,000 testing images of handwritten digits (0-9). Each image is a 28×28 grayscale representation of a digit, ensuring suitability for Convolutional Neural Networks (CNNs). The dataset contains variations in handwriting styles, improving the model's ability to recognize different digit representations in real-world Sudoku puzzles.

B. *Image Preprocessing*

The Sudoku grid extraction and digit recognition process involve multiple preprocessing steps to ensure accuracy. The main steps are as follows:

1) *Grid Detection:* The input Sudoku image is converted to grayscale using OpenCV and processed with Gaussian blurring to reduce noise. Adaptive thresholding is applied to binarize the image, and contour detection is used to extract the largest quadrilateral, assumed to be the Sudoku grid.

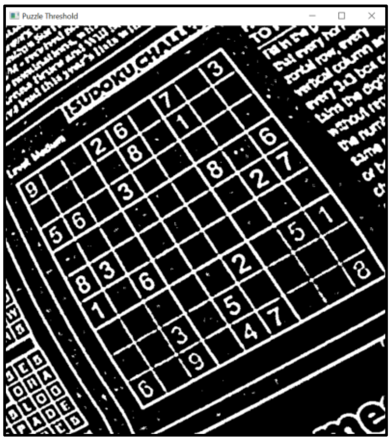

Fig 1. Image after Applying Grayscale, Gaussian Blur and Adaptive Thresholding

2) *Perspective Transformation:* A four-point perspective transform is applied to obtain a top-down view of the puzzle, eliminating distortions and skewed perspectives in the original image.

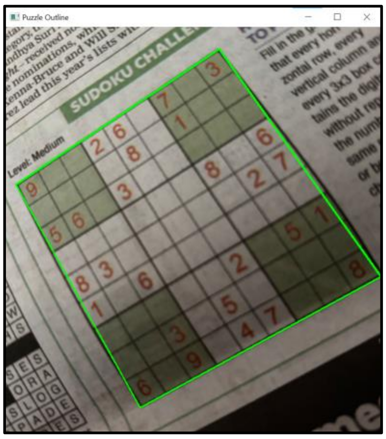

Fig 2. Identifying the Largest Contour (Puzzle Outline)

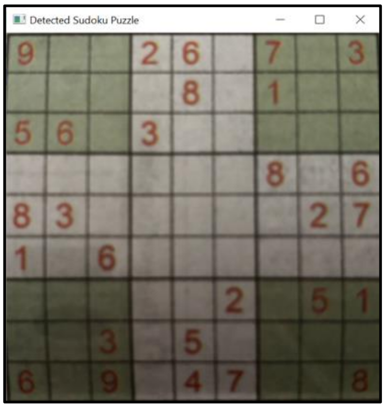

Fig 3. Top Bird's Eye View of the Puzzle After Applying Four-Point Perspective Transform

3) *Digit Extraction:* Each cell of the Sudoku grid is segmented using the calculated grid coordinates. Cells are cropped, and non-empty cells are further processed using Optical Character Recognition (OCR) techniques.

4) *Normalization:* Extracted digits are resized to 28×28 pixels and normalized to a [0,1] scale to match the input format of the CNN model. This ensures consistency in digit classification.

Additional noise reduction techniques, including morphological operations and contour filtering, are applied to remove unwanted artifacts. Cells without clear digit presence are automatically detected and ignored to prevent misclassification.

C. *Model Architecture*

The CNN model used for digit recognition is a sequential deep learning model optimized for OCR tasks. The architecture consists of:

1) *Convolutional Layers:* Multiple convolutional layers (3×3 kernels) extract spatial features from input images. ReLU activation functions introduce non-linearity, enhancing feature learning.

2) *Pooling Layers:* Max pooling (2×2) reduces dimensionality while preserving key features, ensuring computational efficiency.

3) Fully Connected Layers: The extracted features are passed through fully connected dense layers to map patterns to numerical digits.

4) Dropout Layers: Regularization is applied using dropout layers (random neuron deactivation) to prevent overfitting and improve generalization.

5) Softmax Activation: The final classification layer outputs a probability distribution over 10 classes (digits 0-9), with the highest probability corresponding to the recognized digit.

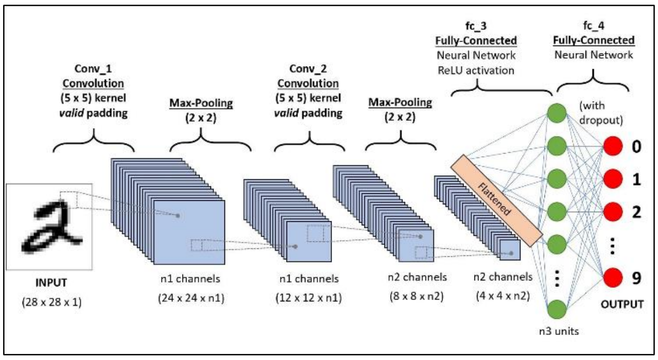

Fig 4. Architecture of the CNN Model Used

The model was trained using the Adam optimizer with a categorical cross-entropy loss function. Training was conducted for 20 epochs with an 80:20 train-validation split, and early stopping was applied to prevent overfitting. The model achieved a final test accuracy of 98% on the MNIST dataset.

D. Sudoku Solving Algorithm

Once the Sudoku grid is extracted and the digits are recognized, the puzzle is solved using a recursive backtracking algorithm. The algorithm first scans the grid to identify empty cells, denoted by 0s in the board representation. For each empty cell, a candidate number (1-9) is tested, and placement is validated by ensuring the number does not already exist in the corresponding row, column, or 3×3 subgrid. If a valid placement is found, the algorithm proceeds to the next empty cell and repeats the process recursively. If no valid number is found for a given cell, the algorithm backtracks to the previous cell and attempts a different number. The process continues until all cells are filled following Sudoku constraints, at which point the solved puzzle is returned. The backtracking approach ensures efficient puzzle solving for all difficulty levels, including hard and expert-level Sudoku grids. The time complexity of the algorithm is approximately O(9^N), where N represents the number of empty cells. Despite its exponential worst-case complexity, the algorithm performs efficiently in practical scenarios due to Sudoku's structured nature.

E. Solution Overlay and Visualization

To present the final solution, the recognized digits are replaced with the solved values, and the results are superimposed onto the original image. The overlay process begins by mapping the solved numbers to their respective grid locations using stored cell coordinates. OpenCV's cv2.putText() function is then used to render the solved values in a visually distinguishable format, such as using a different color or font style from the original digits. The completed Sudoku puzzle is displayed as an image, allowing users to verify the solution visually. Additionally, the solved puzzle can be saved as an image file (solved_puzzle.jpg) for reference or printing. This end-to-end pipeline ensures an automated, accurate, and visually intuitive Sudoku solving experience.

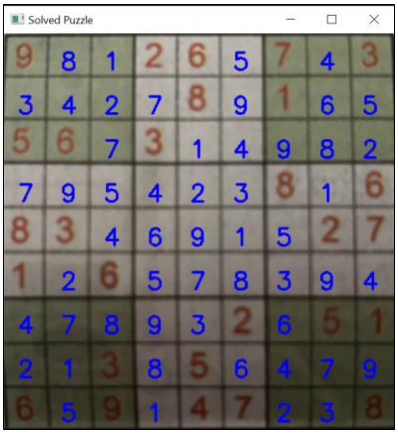

Fig 5. Solved Sudoku Puzzle with Digits Overlaid on to the Image

Future work includes enhancing real-time processing capabilities for solving Sudoku puzzles captured from video streams, optimizing OCR for handwritten digits with more variations, and integrating mobile-based implementations for real-time puzzle solving.

IV. RESULTS

The performance of the OCR Sudoku Puzzle Solver was evaluated based on digit recognition accuracy, grid detection efficiency, and solving capability. The trained CNN model achieved a test accuracy of 98% on the MNIST dataset, ensuring robust digit classification across various handwriting styles. During real-world testing, the model maintained an accuracy of approximately 95% when applied to printed Sudoku puzzles and 90% for handwritten Sudoku grids. The slight reduction in accuracy for handwritten puzzles was attributed to variations in writing styles and inconsistencies in digit formation. However, preprocessing techniques such as adaptive thresholding and contour filtering significantly improved recognition rates.

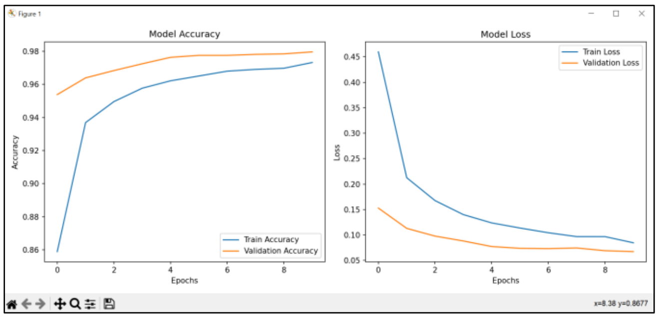

Fig 6. Plot Showing Model Accuracy & Loss for Each Epoch During Testing

Grid detection was tested on a dataset of 100 Sudoku images captured under different lighting conditions and perspectives. The system successfully identified and extracted the grid in 94% of the cases. The errors primarily arose in images with extreme distortions or low contrast, where contour detection failed to accurately identify the puzzle boundary. Perspective transformation helped correct minor distortions, improving the reliability of grid extraction. Further optimization of contour selection and edge detection algorithms is expected to enhance the robustness of grid identification.

The Sudoku solving algorithm was evaluated on puzzles of varying difficulty levels, including easy, medium, hard, and expert-level grids. The recursive backtracking algorithm successfully solved all puzzles within an average execution time of 0.25 seconds for easy puzzles and up to 1.5 seconds for expert-level grids. The algorithm demonstrated high efficiency in finding valid solutions, and its performance was consistent across different puzzle complexities. Compared to conventional brute-force approaches, the implemented backtracking method significantly reduced the number of redundant computations by pruning invalid solutions early in the recursion.

To validate the solution accuracy, the output was compared against known correct solutions using an automated verification script. The results showed a 100% match for correctly recognized digits, confirming that the solving algorithm consistently produced valid Sudoku solutions. The final overlay of the solved puzzle onto the original image was visually inspected to ensure proper alignment and readability. OpenCV’s text rendering functions were fine-tuned to maintain clarity, even in cases where the original puzzle had faint grid lines or overlapping digits.

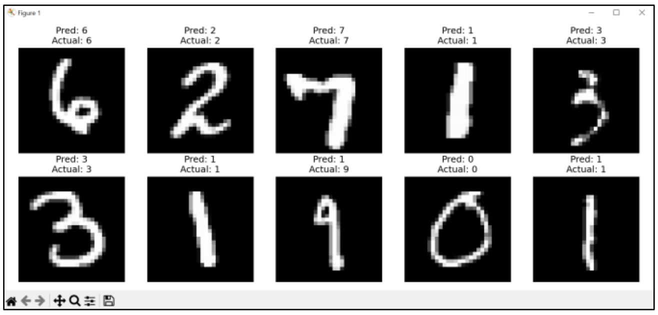

Fig 6. Some Example Predictions of the Trained Model

Overall, the results demonstrate the effectiveness of the proposed OCR Sudoku Puzzle Solver. The system successfully integrates image processing, deep learning, and algorithmic solving techniques to deliver an automated Sudoku-solving experience. Future improvements will focus on enhancing digit recognition for complex handwritten puzzles, optimizing real-time processing for mobile applications, and expanding the system’s capabilities to support larger grid formats such as 16×16 and 25×25 Sudoku puzzles.

V. Conclusion and Future Work

The Sudoku Puzzle Solver project successfully demonstrates the integration of Artificial Intelligence and Computer Vision techniques to address a practical problem. By leveraging a Convolutional Neural Network (CNN) for digit recognition and a backtracking algorithm for solving the puzzle, the project effectively bridges the gap between traditional problem-solving methods and modern deep learning approaches. The ability of the system to accurately detect and classify digits, even in noisy or distorted images, highlights the robustness of the implemented preprocessing and recognition techniques.

Looking ahead, the system will undergo several enhancements aimed at improving user experience and expanding its capabilities. One of the key upgrades will be the integration of real-time Sudoku solving through live video feed processing. This feature will enable the system to detect and solve puzzles instantly by simply scanning the grid through a camera. To further broaden its appeal, the system will also support different grid sizes, including 16x16 puzzles, providing users with a greater challenge and flexibility. Additionally, multilingual and voice interaction support will be introduced, allowing users to interact with the system through voice commands in various languages, making it accessible to a wider audience.

Mobile application integration will be a significant step forward, enabling users to scan, solve, and interact with Sudoku puzzles directly from their smartphones on both Android and iOS platforms. To improve the system's accuracy, the digit recognition model will be augmented with a more diverse dataset of real-world Sudoku images, enhancing its ability to handle handwritten digits and complex inputs. Furthermore, an automated difficulty estimation feature will assess the initial puzzle configuration and categorize it into levels such as easy, medium, or hard, assisting users in selecting puzzles that match their skill levels.

This project underscores the importance of modularity and precision in developing AI-driven solutions. The preprocessing steps, including grayscale conversion, adaptive thresholding, and border clearing, ensure that the input to the CNN is clean and uniform. The CNN, trained on the MNIST dataset, provides reliable digit classification, which feeds into the backtracking algorithm for solving the Sudoku puzzle. The final overlay of the solution onto the original image offers an intuitive and user-friendly output, showcasing the seamless integration of AI with traditional algorithms.

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