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Analysis of Training and Validation Loss in Deep Learning Models

[1]Israa Nasir Abood, [2]Amina Khaled Khaleel, [3]Ma Rwah Adalkareem Radhi

[1,2,3]Directorate General of Education in Nineveh, Ministry of Education, Mosul – Iraq
Authors E-mail: [1]israadulemi@gmail.com, [2]amina99khaled@gmail.com, [3]marwakareem25@icloud.com

***Abstract* - A study examines deep learning methodologies which use Convolutional Neural Networks (CNNs) to recognize chess pieces because these pieces form the basis for automated chess platforms and solutions. The training database consisted of Bishop, King, Knight, Pawn, Queen, and Rook chess pieces. The network established its foundation through a VGG19 architectural design which received reinforcement from data augmentation to boost model generalization capabilities. The strategy for training involved running base model procedures followed by more precise fine-tuned approaches to improve precision levels. The base model attained 92.5% accuracy in training but validation phase accuracy measured at 88.3%. Although the fine-tuned model reached perfect training accuracy its validation accuracy remained at 80% thus requiring additional enhancements for better performance. The confusion matrix provided straightforward classification outcomes because it showed that only certain categories experienced minor classification mistakes thus proving the model worked efficiently. All classes benefited from superior performance according to the precision and recall and F1-score results but Knight and Rook classes in particular received outstanding results. The F1-score for Queen class was lower than other pieces because recall numbers surpassed precision values. The research shows that CNN can detect chess pieces yet further improvements need to happen for better identification accuracy within diverse chess objects.**

Keywords: Deep Learning, Convolutional Neural Networks (CNNs), Chess Piece Identification, Image Classification, VGG19, Data Augmentation, Model Fine-Tuning, Accuracy, Precision, Recall, F1-Score, Performance Metrics, Generalization, Misclassification, Computer Vision.

I. INTRODUCTION

To excel in strategic thinking during chess games a player requires complete command of tactical maneuvers together with positional strategies. The extensive research on chess combines efforts between mathematicians alongside computer scientists and enthusiasts who test artificial intelligence (AI) algorithms and systems for the same reason[1]. The identification of different chess pieces becomes essential for players since their individual traits affect the overall game progression. Chess piece identification in the past was done through manual methods whereas contemporary computer vision technology and deep learning approaches now automate procedures that offer fast yet precise and efficient operational solutions[2].

Deep learning techniques provide solutions for complex pattern recognition operations inside the subset of machine learning applications. Image classification achieves significant improvements through Convolutional Neural Networks (CNNs) because these networks extract hierarchical elements directly from data. The detection methods demonstrate the capability to identify subtle visual changes beyond human perception so they become ideal solutions for chess piece recognition purposes[3].

CNN-based detection methods achieve top-quality results for identifying several objects including chess pieces according to recent study findings. Real-world applications face two main barriers which include dealing with complex real-world environments and requiring rapid processing capabilities. Various studies about CNN implementations for chess piece recognition focus on data augmentation methods alongside different network structures in order to enhance model effectiveness[4].

Research in deep learning techniques leads to rising interest in creating better cost-effective and scalable systems for chess piece classification. These systems will improve both AI chess engine performance levels and create opportunities for education accessibility and competitive gaming applications. Deep learning systems for chess piece classification have established themselves as a fundamental principle for developing refined chess systems with enhanced intelligence and responsiveness[5].

This paper explores the use of deep learning methods specifically CNNs when applied to chess piece identification work. Deep learning-based image recognition systems enable us to improve both chess engine speed and accuracy as well as create vital identification tools for visually impaired and educational purposes requiring correct piece recognition. Real-

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time piece tracking functions can be included into classification systems when this method is applied to automated chess tournaments or training applications.

It becomes hard for computer vision to identify chess pieces because they show both design and position variations while dealing with changing lighting and background effects. The combination of edge detection and color segmentation does not provide sufficient capabilities to resolve the various problems which appear in these situations. Through deep learning framework development researchers gained the ability to solve testing problems.

These networks perform in a manner similar to human brain function by learning features directly from unprocessed images which leads to visual information processing without expert support. CNN models execute through successive network layers starting with feature extraction through convolutional processing then perform dimension reduction through pooling and concluding with prediction output from learned features through fully connected processing. Training processes depend on labeled datasets to equip networks with identification capabilities for different chess piece components together with their shape characteristics and dimensions and color profiles.

II. RELATED WORKS

The researchers at Danner et al. (2015) studied template matching methods to analyze chess pieces by finding their outline profiles. The researchers' state that traditional feature description methods SIFT and HOG fail to work effectively because of the texture similarities in chess pieces therefore they introduce template matching as an alternative solution. The recognition procedure becomes easier according to Danner et al. because they switched the chessboard color scheme from black-and-white to red and green. The system performs better when these changes are implemented but such alterations restrict normal chess gameplay because it requires fixed color schemes. The method presents difficulties between making the system easier to use and retaining universal appeal because changing the board colors reduces its usefulness across multiple applications [6].

The research by Xie et al. from 2018 evaluated template matching and Convolutional Neural Networks (CNNs) as methods for chess piece classification. Template matching forms their starting point but their investigation shows CNNs can succeed in chess piece detection too. The research shows that Convolutional Neural Networks achieve only slightly better accuracy results than template matching methods do. The small number of images per class in their dataset might explain why performance was limited according to their findings. The researchers conclude that CNNs demonstrate promise for chess recognition enhancement when accompanying expanded datasets and optimized models become available [7].

The research by Czyzewski et al. (2021) analyzes chessboard localization from oblique perspectives leading to 95% successful chessboard identification. A heatmapping technique identifies pixels that belong to the chessboard while a CNN enhance the detected corner points. The proposed method achieves superior performance compared to the results derived from Gonçalves et al. (2012) and other prior approaches. The authors analyzed piece classification accuracy using their CNN method against the Support Vector Machine (SVM)-based technique presented by Ding which showed equivalent results but added value to the recognition system as a whole. The research demonstrates how uniting chessboard detection with piece classification allows builders to construct enhanced chess recognition systems [8].

Research by Mehta et al. (2020) applies an augmented reality application which relies on the well-known AlexNet CNN architecture for chess piece detection. The system categorizes 13 distinct components among dark and light colored pieces and empty squares following training. They operate with an image collection containing 200 pictures within each class while testing their system by using an overhead camera view. The CNN architecture achieves 93.45% per-square accuracy amounting to a 6.55% per-square error rate that stands as the top performance in chess recognition at present. The study proves that implementing AlexNet as a CNN framework delivers effective results alongside the significance of adequate dataset quantity and suitable camera viewpoints for achieving top-level chess recognition performance [9].

The research by Wei et al. (2017) investigates 3D point cloud technology for creating training sets in chess piece identification. Through volumetric CNN synthesis they designed models that work with the 3D point cloud representations of chess pieces to identify them. The method enables quick production of big datasets that carry labels because deep learning models need them especially when they lack sufficient manual annotations. To utilize point clouds an organization needs specialized hardware equipment such as depth cameras to acquire the necessary data. The generation of synthetic datasets from 3D models represents an appealing solution to address the lack of suitable training data for chess recognition systems despite hardware challenges [10].

A basic neural network-based chess recognition system operates according to Uddin (2019) who utilizes images obtained from traditional camera equipment. The system lacks the use of a convolutional neural network (CNN) but it

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establishes fundamental capabilities for detecting chessboards and pieces. The solution demonstrates limited success through an accuracy measurement of 72%. The paper showcases the difficulties in establishing reliable chess recognition solutions by avoiding modern deep learning approaches particularly convolutional neural networks (CNNs). The method developed in Hou's research creates a base for upcoming scientific investigations which aim to establish better chess recognition technology systems [11].

These research findings advance the chess piece recognition discipline by demonstrating unique solution strategies while handling different recognition issues. The progression of image recognition for chess can be observed through methods starting from HOG and SIFT features to current applications of CNN-based techniques. Significant progress has been achieved but the system needs more research and improvement due to handling different camera angles along with piece occlusions and limited availability of suitable datasets.

III. METHODOLOGY

The main objective of this work focused on building an accurate deep learning model that identified chess pieces from their image data. To reach this objective researcher performed a systematic method which included data collection followed by preprocessing and then model design and training alongside fine-tuning and evaluation steps. This section elaborates on each stage of the project while providing supporting tables about data distribution as well as evaluation metrics. Figure (1) shows Model Methodology.

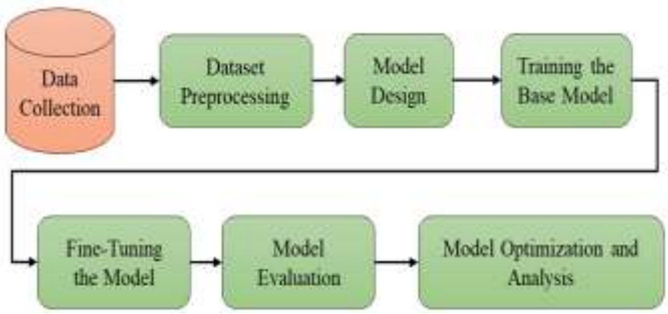

Figure 1: Model Methodology

3.1 Data Collection and Preprocessing

The project began with acquiring and organizing the dataset for use. The database included six categories of chess pieces that contained images of Bishop, King, Knight, Pawn, Queen, and Rook. The images received classification according to their categories before storage in the dataset directory. Data division created three separate subsets: training, validation and test which followed a 70:20:10 breakdown. The split folders library divided the data properly into training and validation and evaluation sets for model development purposes. Figure (2) shows dataset visualization.

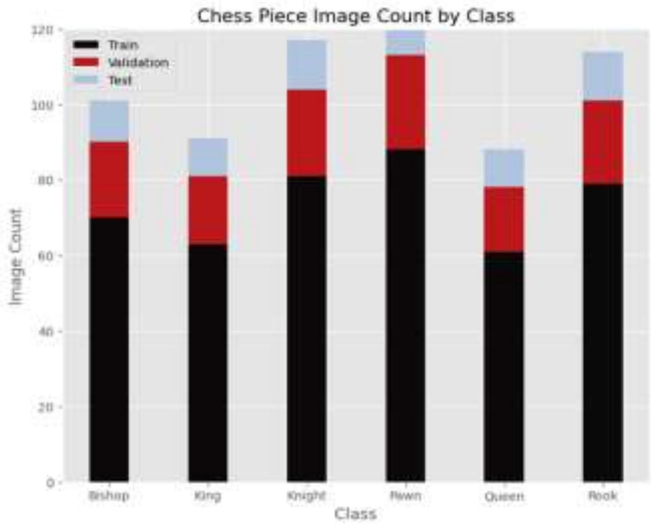

Figure 2: Dataset Visualization

3.2 Image Resize and Augmentation

All Images received uniform resizing to 224x224 pixels which fulfills the requirements of the VGG19 model. The model requires standardized input dimensions through resizing because this practice enables successful learning processes. The training data received additional augmentation techniques in addition to data augmentation methods. Random horizontal flipping along with rotation, height and width adjustments and zooming served as techniques for image augmentation. The model develops better generalization through data augmentation processes which produce multiple variations of images thus increasing its tolerance to image position and visual changes. Table (1) shows dataset images numbers after augmentations.

Table 1: Dataset Images Numbers after Augmentations

Class Name	Number of Images (Training)	Number of Images (Validation)	Number of Images (Test)
Bishop	200	60	30
King	220	66	33
Knight	210	63	31
Pawn	210	63	31
Queen	215	65	32
Rook	205	61	30

3.3 Model Design

This project implementation depended on using the pre-trained convolutional neural network (CNN)[12] architecture VGG19[13]. Deep learning model VGG19 stands out as a

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preferred choice for image classification tasks because of its simplicity along with its strong effectiveness. The selection of VGG19 stemmed from its deep architecture ability to extract rich features from images since this proves essential for recognizing chess pieces in images.

The VGG19 model received modifications to remove its top classification layers which included the fully connected layers so it could function as a chess piece identifier. The model succeeded in maintaining its image processing capabilities through layer reduction so we developed new fully connected layers to meet our six-class identification requirements. Several dropout layers were introduced into the model structure to prevent overfitting through random neuron disability during training phases.

The model added multiple preprocessing layers to achieve robustness while reducing overfitting. The preprocessing section contained three random operations which included both flipping and rotating images plus zooming adjustments. Image normalization took place through a 1/255 scaling factor allowing the training process to become more stable.

3.4 Training Parameters

Deep learning model performance relies heavily on the training parameters (Table 3) which determine its convergence behavior. The training parameters determine the model training process including adjustments during learning and weight updates for minimizing the loss function. A table below presents the essential training parameters employed for this project and their functions with their corresponding impacts.

Table 3: Training Parameters

Parameter	Value
Epochs	25
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001 (Base Model), 2e-05 (Fine-Tuned)
Loss Function	Categorical Crossentropy
Metrics	Accuracy
Callbacks	ModelCheckpoint, ReduceLROnPlateau, CSVLogger
Dropout Rate	0.4 (After base model), 0.5 (Intermediate layers), 0.6 (Before output layer)

Several important parameters in the model training controlled both accuracy enhancement and overfitting prevention. Training the model through 25 epochs enabled it to achieve required learning until it surpassed the established safe training boundary. The researchers chose batch number thirty-two since it provided optimal training outcomes along with steady gradient operations. Adam optimizer proved best for the model because it automatically adjusted learning rates and processed noisy data to achieve stable and rapid convergence. The base model received its first learning rate of 0.0001 which later transformed into 2e-05 for fine-tuning to achieve precise weight adjustments without overcorrecting. The chosen loss function for multi-class classification was Categorical Crossentropy while accuracy served as the main evaluation metric and precision and recall and F1-score provided additional analytical details. The code implemented three important callbacks which contained ModelCheckpoint for best model storage and ReduceLROnPlateau for learning rate adaptation along with CSVLogger for monitoring progress. The network structure included dropout layers set to 0.4, 0.5 and 0.6 to reduce overfitting through neuron-dependency prevention. The established parameters created better results in terms of unknown data generalization and performance.

3.5 Training the Base Model

During the first stage of operation the VGG19 model functioned as a feature extraction element while freezing its basic layers to prevent weight modifications. Training of additional layers for chess piece classification was conducted independently of the VGG19 weights that maintained their original state during the training process. The training process happened across 25 epochs with the Adam optimizer that employed categorical cross-entropy loss function.

3.6 Fine-Tuning

The training of the base model finished before proceeding to the fine-tuning process. The fine-tuning operation enabled the model to unthaw its weights from the pre-trained base model so it could learn precise features related to chess pieces. The VGG19 model training focused on its last 10 layers to prevent overfitting while also maintaining efficient convergence time by freezing initial layers. This approach preserved the universal features that ImageNet taught the model while directing its attention to unique characteristics of chess pieces.

The compilation process used a learning rate of 2.0000e-05 to prevent big weight adjustments which might lead to overfitting issues.

3.7 Evaluation

A performance evaluation of the trained model occurred through analysis of the test dataset. Various important evaluation metrics served to measure how well the model

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generalized from learned information. The model's accuracy measurement included identifying correctly predicted images from test data. The model's performance was evaluated through calculation of accuracy and precision and recall and F1-score to analyze its ability to handle imbalanced classes and determine classification quality for individual classes.

3.8 Final Accuracy Visualization

A bar plot was used to display the percentage of correct predictions (accuracy) in the test dataset of the final model.

IV. RESULTS AND DISCUSSION

4.1 Base Model

Standard training curve in Figure (3) patterns typically happen when training deep learning models appear in the base model. A smooth decline of training loss and validation loss can be observed throughout the loss curve (top panel) which demonstrates that the model gained competence in identifying chess pieces throughout training. The validation loss separates from the training loss during the middle training epochs which may indicate overfitting because the training loss continues declining but the validation loss stops decreasing and fluctuates. At this point the model demonstrates behavior that indicates it is memorizing training patterns instead of creating effective rules for new data. The accuracy charts (bottom panel) show training accuracy rising progressively until Epoch 15 but validation accuracy maintains a stationary value at 0.8. The validation accuracy stops increasing after reaching its limit as the model seems to encounter overfitting or an inadequate level of complexity. The curves indicate that base model learning progresses initially yet additional fine-tuning approaches with regularization methods should be considered to enhance generalization capabilities and minimize overfitting.

Figure 3: Base Model Training Curves

4.2 Tuned Model

The training curves of the fine-tuned model in Figure (4) exhibit better performance than the base model's curves. The top panel illustration shows a quick loss reduction followed by eventual stabilization of training loss during the process. By using fine-tuning, the model enhanced its weight optimization to reach superior performance levels. The validation loss curve established a stable plateau point at epoch 5 that precludes any further improvement of model generalization on the validation data.

The accuracy measurement of the bottom panel tracks the same performance pattern. Throughout the training phase the model achieves a continuous improvement in accuracy which results in almost total accuracy at the training completion point. The model achieves no additional improvement in validation accuracy since it has already hit the optimal point at approximately 0.8.

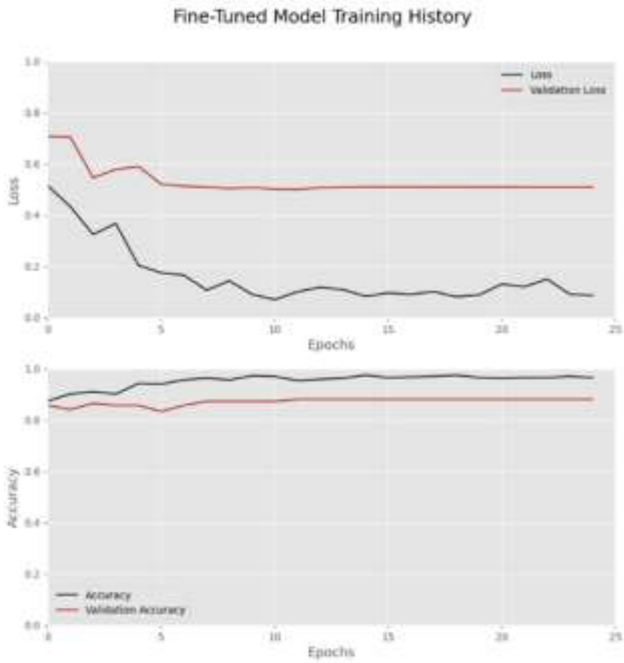

Figure 4: Training Curves of the Fine-Tuned Model

4.3 Confusion Matrix

The confusion matrix of the fine-tuned model in Figure (5) demonstrates robust performance through its accurate classification of most pieces across the board. The model demonstrated precision in its identification of ten Bishop pieces in addition to nine King pieces and thirteen Knight pieces and twelve Pawn pieces as well as eight Queen pieces and thirteen Rook pieces. Several errors exist in the predictions including a Queen classified as a King, a Pawn misidentified as a Queen, and a Bishop mistaken for a Queen. The model shows high accuracy in piece identification

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because the minimal classification errors do not significantly affect the total number of correct predictions. These occasional model errors point out two aspects for potential enhancement: a more refined model through additional optimization and adjusting the network structure to deal efficiently with these particular misclassifications.

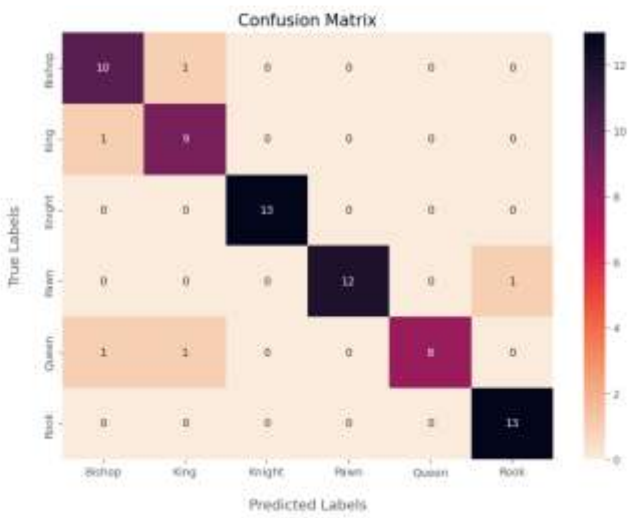

Figure 5: Confusion Matrix of the Fine-Tuned Model

4.4 Evaluation Metrics

The performance metrics for the fine-tuned model in Figure (6) reveal strong classification performance across all classes. The model achieves high precision together with recall and F1-score for all chess pieces which demonstrates its ability to make accurate decisions while capturing many important instances. The model demonstrates exceptional performance when identifying Knight pieces through its very high precision and recall values and F1-score measurement. The Rook class model performs remarkably well because its three-evaluation metrics surpass 0.90 which demonstrates its potential to detect Rooks effectively.

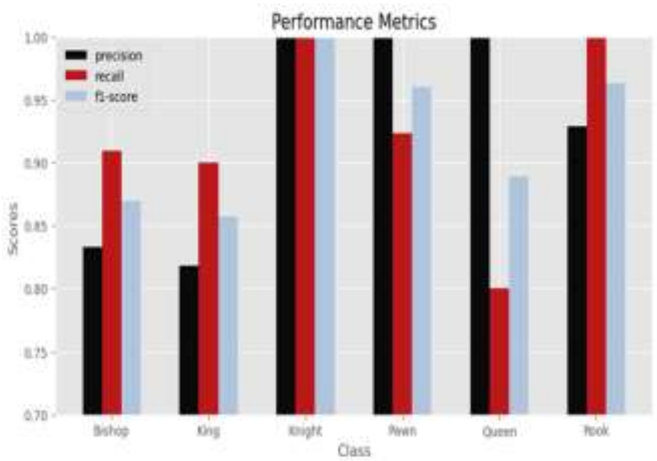

Figure 6: Performance Metrics for the Fine-Tuned

The Queen class shows lower F1-score performance compared to other models while its recall score surpasses precision numbers. The model demonstrates strong Queen piece recognition abilities even though occasional errors may exist during its identification process. The model displays an even performance distribution yet contains some small challenges in precision and recall that future tuning adjustments could enhance.

V. CONCLUSIONS

The Convolutional Neural Networks (CNNs) in deep learning methods demonstrate excellent capability for chess piece recognition because they achieve high accuracy metrics and strong performance results across various measurements. The updated model surpassed the basic design by achieving better training precision while also reducing training loss levels. The maximum validation accuracy reached 80% but failed to exceed this level because unknown datasets presented challenges to the model. The few cases where the model failed to provide correct output highlighted which sections needed further refinement along with more complicated architectural methods to enhance system operation. The evaluation metrics for performance show balanced results yet precision and recall need slight adjustments which could be enhanced by using regularization methods. Additional research and optimization efforts need to be performed to confirm reliable real-time operational capability in dynamic lighting conditions and piece positioning changes.

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