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A deep learning approach for multi-class classification of handwritten prescription images using CNN and Grad-CAM visualization

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Abstract
The identification of handwritten prescriptions is increasingly regarded as an important task during the digitization process occurring within healthcare. Written prescriptions are estimated to account for more than 13% of prescription errors. This research proposes a convolutional neural network (CNN)-based classification approach for the automatic classification of handwritten prescription drug images to a total of 78 classes. The dataset contains 60 images per class, 20 of which were used to train the network, 10 of which were used for validation, and the remaining 10 were used for testing. All images were resized to 64 × 64 pixels and converted to grayscale to provide input into the model. The CNN configuration achieved 80.38% validation accuracy and 69.74% testing accuracy. In order to interpret model outputs, Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to highlight class-relevant areas of the images. The last component of this work evaluated and analyzed the model using confusion matrix analysis, accuracy per class, and misclassification patterns. Ultimately, this work indicates that the proposed method is feasible for the recognition of handwritten prescription and provides new information for the future practical application of this task in medical systems. This initial work is an important contribution to the growing area of AI-assisted medicine, providing an interpretable and scalable solution to drug identification.

Keywords: Handwritten prescription classification, convolutional neural network (CNN), deep learning, Grad-CAM visualization, multi-class image recognition

1. Introduction

1.1 Background

Digital technologies have brought changes to the healthcare system over the last few decades in three predominant modes: medical records, readings (measures), and drugs [1-4]. Legitimately reading handwritten medical prescriptions remains a contemporary challenge, which has immediate implications for the safety and productivity of pharmacies [5]. Handwritten prescriptions are still prevalent in many areas of practice, and the illegibility of handwriting, obscure names of drugs, and interpretations of abbreviations or symbols can all be sources for errors in reading the prescription [6]. These now are the basis for medication errors that contribute to preventable harm [7].

As health care infrastructure improves, there is an increasing demand for automation solutions able to accurately process prescription data and, in particular, prescription medication names [8]. In addition to consuming an exorbitant quantity of time, human manual data entry is also inherently error prone. For these reasons, academics and professionals have begun to turn towards artificial intelligence (AI), more generally deep learning, to alleviate some of these issues [9]. Convolutional Neural Networks, which are a type of deep learning structures by nature well-suited in design for image analysis tasks, enjoy exceptional performance in application scenarios including handwriting recognition, object detection, and medical imaging. CNNs are capable of automatically learning spatial hierarchies and features from image data, making them ideal candidates for interpreting complex handwritten inputs without extensive manual feature engineering [10].

Success in application of CNNs in postal code detection, number plate detection, and even in pathological image classification has paved a way for likely application in pharmaceutical cases as well [11]. While applying CNNs on prescription data in handwriting comes with a variety of domain-specific issues, they encompass intra-class variability (e.g., differential handwriting of same name for a medicine), classes that are similar in appearance (e.g., almost identical looking medicine names), background noise, as well as non-uniform illumination conditions in scanned or photographed images. Also, a great number of medicines have prefix/suffix appearances that are highly similar, which is likely going to lead to misclassifications by poorly discriminative models [12].

Also, several works examined optical character recognition (OCR) technology for distinguishing text in prescriptions, but, as a solo effort, OCR fails when it encounters unstructured writing or cursive writing [13]. To address this constraint, the field has shifted toward image-based deep learning methods. By treating the entire drug name as a visual pattern rather than characters to be accurately segmented, CNNs focus on overall visual characteristics that are most robust for classification [14].

Concurrently, interpretability and trust in AI models have become important demands in medical applications. High accuracy of a model is insufficient; healthcare professionals and regulators want to know how the model reaches a decision. Grad-CAM (Gradient-weighted Class Activation Mapping) and other mechanisms have been proposed as solutions. Grad-CAM provides visual explanations for predictions by highlighting the regions in an image that are most influential for the model's decision. Such visualizations can help pharmacists and clinicians validate the correctness of a model's output, thereby increasing confidence in the system [15, 16].

Furthermore, the advancement of open-source libraries, availability of GPU computing, and accessible deep learning frameworks like TensorFlow and PyTorch have democratized the development and deployment of CNN models. Due to these tools, it is now possible for large training, real-time inference, and rapid prototyping, enabling real-world deployment in mobile devices, point-of-care devices, and in pharmacy systems [17, 18].

As a part of this, our investigation presents a solution for identifying handwritten medication name using a CNN, applied across a multi-class dataset of 78 commonly prescribed medication images. The problem is not only addressed for obtaining high-accuracy classification but is approached with a further goal of enabling visual interpretation of output, thus creating a reliable aid for assisting pharmacists and healthcare professionals in prescription verification and digitization.

Despite advancements in optical character recognition (OCR) and image processing, existing systems are not capable of accurately categorizing handwritten drug names due to diverse writing styles, class imbalance, and low-resolution images. Drug name misclassifications have traditionally serious patient safety implications in addition to compromising reliability in automated prescription systems. Furthermore, a great proportion of existing models have high precision but are not interpretable, which is not useful in clinical practice where it is necessary for clinicians to be aware of decisions made by models.

1.2 Problem Statement

Despite the advances in OCR and image processing, current systems still face challenges in recognizing handwritten drug names accurately because of the variations of handwritten patterns, imbalance of different drug classes, and low resolution of input images. Mislabeling drugs is very dangerous for the patients and reduces the reliability of the automatic prescription systems. Moreover, some of the models available today are highly accurate but not interpretable; this will not be acceptable for a clinical background where it is necessary to understand the potential decisions of a model.

1.3 Research Objective

The objective of this study is to create a strong and understandable CNN-based model for sorting handwritten drug names taken from prescription images. The main goals are

- Preprocessing and standardizing the prescription image dataset to enable effective CNN training.
- Designing and evaluating a deep learning model capable of classifying 78 distinct drug classes with high accuracy.
- Applying Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize and interpret model decisions, enhancing trust and transparency in medical AI systems.
- Delivering comparative performance assessment and confounding effects to showcase the model's opportunities and constraints in practice.

Literature Review

In recent years, there has been remarkable progress in deep learning in detecting and interpreting handwritten prescriptions in medicine. Researchers have experimented with numerous neural network architectures, including CNN, Bidirectional Long Short-Term Memory (Bi-LSTM), and hybrid models of CNN with LSTM or Recurrent Neural Network (RNN) layers in an effort to address the issues of illegible writing and to support multiple languages [19]. To enhance the accuracy and resilience of these models, the deep learning models have been trained using multiple datasets and fine-tuned using methods like data augmentation, transfer learning, and lexicon based decoding [20]. Attention mechanism, fuzzy search algorithms, and multilingualism also feature, that makes these systems more usable in practice-based health care. This comparison is summarized in Table 1.

Table 1: Summary of Recent Deep Learning Approaches for Handwritten Medical Prescription Recognition.

Reference	Year	Model Used	Dataset/Technique	Accuracy/Results	Contribution
Jain *et al.* [21]	2021	CNN-BiLSTM + CTC	Prescription dataset; string matching	Improved recognition of medical terms	Used CNN-BiLSTM for structured text extraction
Tabassum *et al.* [22]	2021	Bidirectional LSTM + SRP Augmentation	Handwritten Medical Term Corpus	89.5% accuracy	SRP data augmentation boosted accuracy
Shaw *et al.* [23]	2021	Neural Network	Extended MNIST	Efficient recognition	Converted illegible handwriting to digital text
Malbog *et al.* [24]	2022	SSD Mobilenet v2	Doctor samples (handwritten)	92.4% accuracy, 57.4 ms speed	Developed a device for drug name recognition
G *et al.* [25]	2022	CNN, RNN, LSTM	Multi-language, Unicode Matching	Multilingual capability	Prescription recognition in any language
Pavithiran *et al.* [26]	2022	CNN, RNN, LSTM + Fuzzy Search	Multi-language Handwriting	Structured output	Used fuzzy search and basket analysis
Shahade *et al.* [27]	2023	CNN	Custom dataset	89% training, 70% test accuracy	CNN-based text extraction from prescriptions
Honey *et al.* [28]	2023	AlexNet + SVM	Transfer learning	98% accuracy	Recognition + alternative drug suggestions
Zia *et al.* [29]	2023	Transformer-based, GB, RF, Ridge	Custom handwriting dataset	0.85 accuracy	Sequence-to-sequence for medicine extraction
Sehimi *et al.* [30]	2023	CNN + BiLSTM + CTC	Transfer learning	Performance enhanced	BiLSTM + CTC for sequence labeling
Razdan *et al.* [31]	2023	CNN + BiLSTM + Lexicon Search	Handwritten prescriptions	Improved recognition	Lexicon Search improves decoding
Kavinda & Fernando [32]	2024	VGG + BiLSTM	Prescription Dataset	83% accuracy, 0.4874 loss	VGG-based sequence recognition
Khan *et al.* [33]	2024	CNN + BiLSTM + CTC	Handwriting dataset	98.4% accuracy	Hybrid CNN-BiLSTM for high precision
Ramani *et al.* [34]	2024	CNN + FLSTM	Multilingual prescription	High accuracy	AI-powered decoding and safety enhancement
Dhayanithi *et al.* [35]	2024	MobileNet	Pill recognition images	High accuracy	Automated pill detection system

As shown in Table 1, several deep learning models have been utilized in available literature, including CNNs, Bi-LSTMs, and hybrids, for handwritten prescription recognition issues. Although many methodologies have proved promising in terms of accuracy, they tend to be based on elaborate architecture, large numbers of datasets, or narrowly focused on a small number of languages or predefined word classes. However, this paper contributes by offering a lightweight and implementable CNN-based scheme specially designed for multiclass handwritten drug name classification based on a carefully selected dataset of 78 classes. With the advantages of high-resolution preprocessing, learning rate scheduling adaptation, and explainability as Grad-CAM, this design balances accuracy, generalizability, and efficiency in a trade-off manner. In addition to addressing the need for prescription digitization for a variety of medicine labels, the article serves as a foundation for real-time healthcare application scenarios in settings with limited resources.

3. Methodology

3.1 Overview of Methodology

The methodology in this study is based on a structured pipeline for accurate classification of handwritten images of drug names. The process begins with the collection of a dataset of 78 drug classes containing handwriting samples of prescription images. Each handwritten drug name image is then pre-processed to ensure a uniform size and bias free format. The images will be split into training, validation and test subsets.

A customized CNN is created to learn important visual traits, and batch normalization and the dropout technique are employed to improve the model's generalization. The model is compiled with categorical cross-entropy for loss function and Adam as an optimizer. The model is trained for 50 epochs using learning rate scheduling to avoid over-fitting. The model's performances are analyzed using accuracy, loss curves, classification reports, and confusion matrices. Grad-CAM is utilized to visualize which regions are influencing the model's decision.

The complete pipeline is illustrated in the expert workflow diagram (Figure 1).

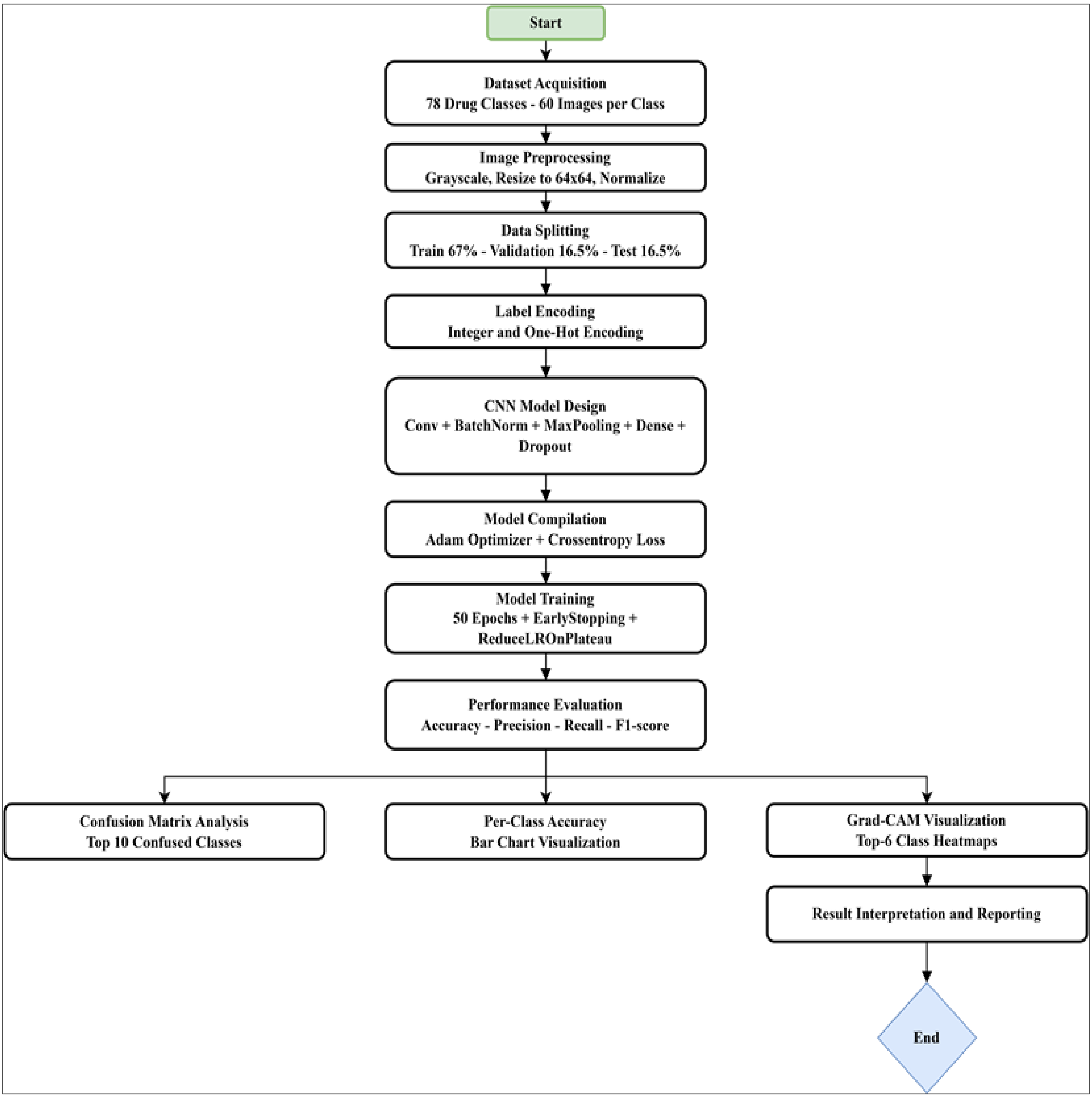

Fig 1: Expert workflow showing the complete methodology pipeline for handwritten drug name classification using a CNN-based approach.

3.2 Dataset Description

The data where this study draws its examples contained handwritten prescription images representing 78 different drug classes [36]. Each drug class had approximately 60 grayscale images for a total of 4,680 samples within the data. The data was split into training, validation, and test subsets, while keeping a balance across each class with the purpose of effective model evaluation. All images were resized to 64×64 pixels and normalized to the [0, 1] range for CNN processing.

The class-wise distribution and partitioning of data have been presented in Table 2, and a sample visualization of selected images of drug names from class is presented in Figure 2. The images are provided to demonstrate the visual variations of handwriting, and the variable nature of look-alike drug names creates a classification problem.

Table 2. Dataset Composition and Split by Class.

Split Type	Number of Images per Class	Percentage of Total
Training Set	40	~67%
Validation Set	10	~16.5%
Test Set	10	~16.5%
Total	60	100%

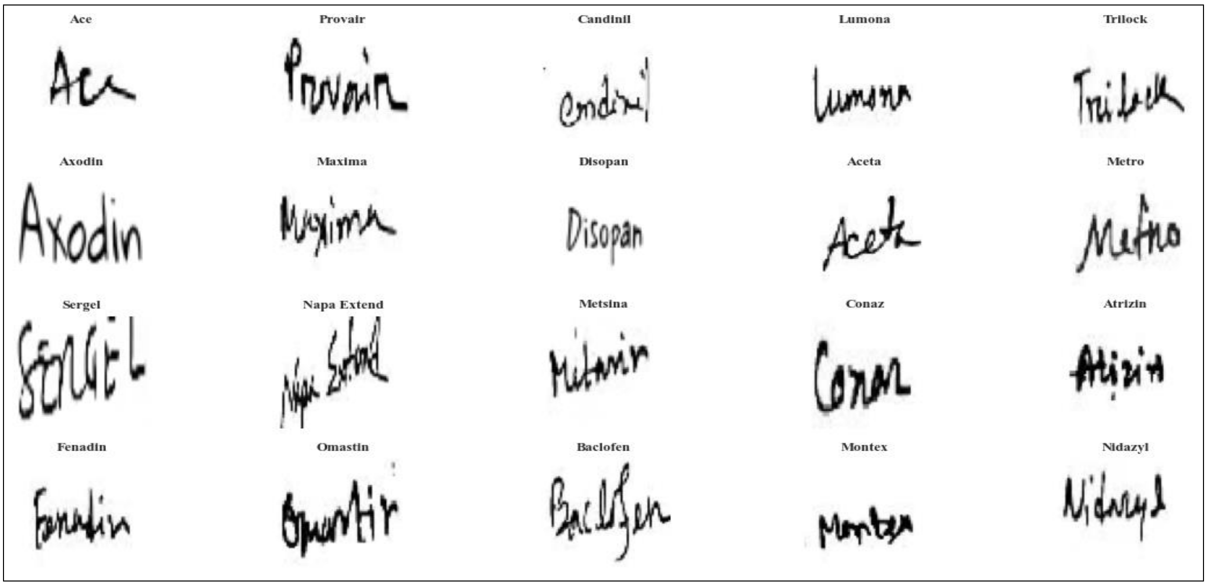

Fig 2: Sample images of handwritten drug names across 20 different classes. [36]

3.3 Data Preprocessing

To facilitate compatibility with the CNN architecture, the data also underwent a preprocessing step in which each drug names' handwritten images were resized to 64×64 pixels and converted to grayscale (see figure 3.) Pixel intensity values were then normalized to the range [0, 1] by dividing by 255, which facilitates faster and more stable convergence during training.

The corresponding class labels, originally provided as textual drug names, were encoded into numerical form using a label encoder. Then these numerical labels were encoded into a categorical one-hot representation to facilitate multi-class classification over a total of 78 classes.

To maintain consistency and avoid bias during training and testing of models, stratified sampling was applied in partitioning the dataset into training, validation, and test sets. This resulted in all subsets having a proportionate and uniform distribution of all classes, hence allowing for improved generalization of the model on novel data.

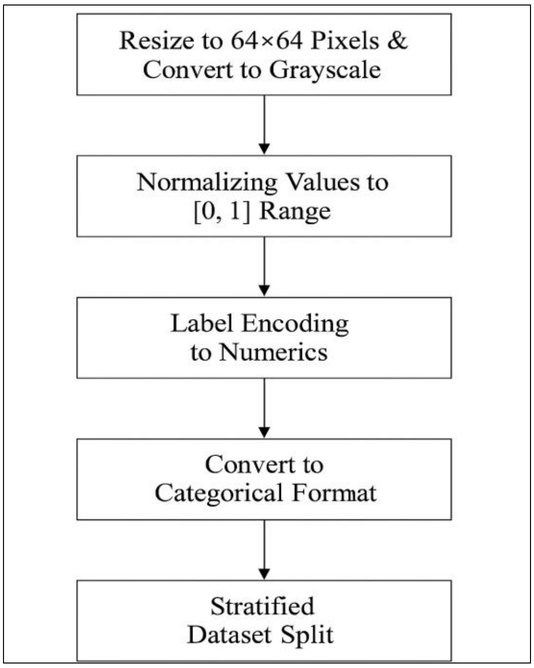

Figure 3. Data Preprocessing Workflow.

3.4 Model Architecture and Training Configuration

A custom CNN-driven architecture for precise classification of all images of handwritten drug names into 78 distinct classes. The network was carefully built for a complex-generalization strength trade-off, minimizing overfitting as much as possible.

The network consists of three successive convolutional blocks. Each block consists of a Conv2D, a subsequent batch normalization, and a MaxPooling2D. This serves to allow the network to extract hierarchically spatial features in a way that stabilizes training as well as helps reduce internal covariate shift.

The resulting 3D output feature maps are passed on to a Flatten layer in order to flatten them into a 1D feature vector, which serves as input for a fully connected Dense layer of 256 units with ReLU activation. A dropout layer is included after the dense layer to reduce overfitting by randomly deactivating neurons during training.

The final output layer is a dense layer with 78 units, corresponding to the number of drug classes, using the softmax activation function to generate probability distribution over all classes.

The complete model comprises approximately 1.29 million trainable parameters, all optimized using the Adam optimizer with an initial learning rate of 0.0001.

To optimize the model (Figure 4), the following training strategy was employed:

- **Loss Function:** Categorical Cross-Entropy, suitable for multi-class classification tasks.
- **Optimizer:** Adam, selected for its adaptive learning capabilities and efficient convergence.
- **Batch Size**: 32 samples per batch.
- **Epochs:** The model was trained for up to **50 epochs**.
- **Learning Rate Scheduling:** A ReduceLROnPlateau strategy was utilized to decrease the learning rate once the validation performance plateaued.
- **Early Stopping:** Used to stop the training when the validation loss did not improve to avoid overfitting.
- **Checkpointing:** The model that performed best based on validation loss was saved for final evaluation.

This architecture facilitated the model to converge effectively while maintaining generalization on test data it had not encountered in the training data.

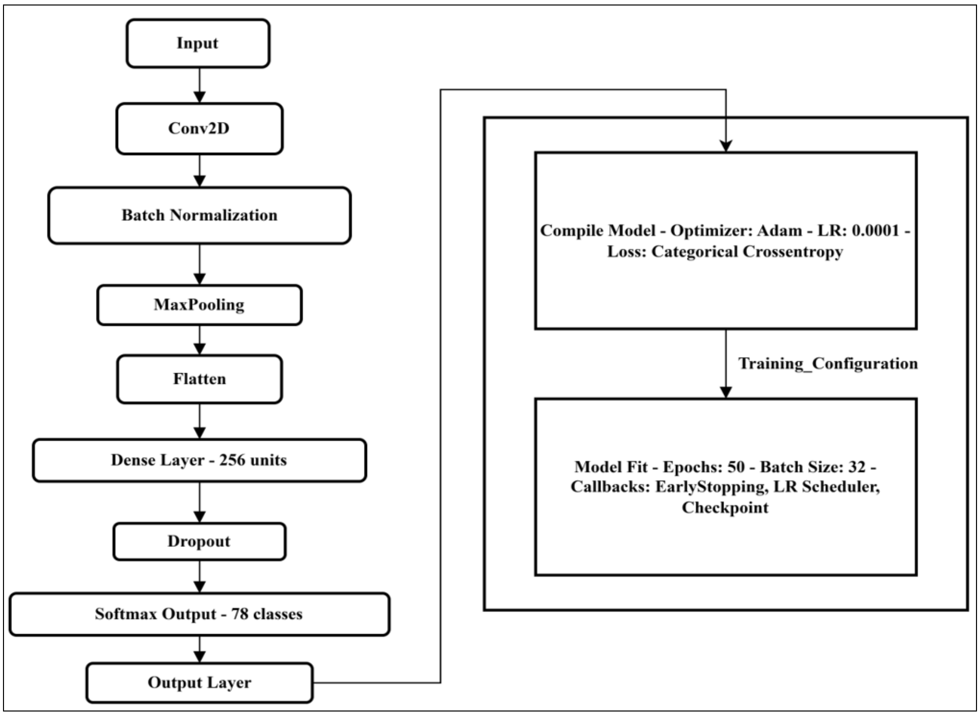

Fig 4: CNN Architecture Overview and Training Configuration.

Performance Evaluation Metrics

The assessment of the proposed CNN model was rigorously undertaken via a range of quantitative and visual metrics, in order to achieve a robust assessment and interpretable analysis.

The evaluation components are given below:

- **Accuracy:** Calculated for each of the training, validation and test datasets, measuring overall classification correctness.
- **Loss Analysis:** Training and validation loss curves were plotted across 50 epochs to track model convergence, while detecting signs of over- or under-fitting.
- **Classification Report:** Precision, recall and F1-score were computed for every one of the 78 classes, providing detailed insights into the model's performance on a per class level.

- **Confusion Matrix:** Presented in three formats:
- Raw confusion matrix with actual prediction counts,
- Normalized confusion matrix to visualize relative error distribution.
- Top 10 class confusion matrix highlighting the most misclassified drug names.
- **Per-Class Accuracy:** A bar chart displaying the accuracy score for each class to identify strengths and weaknesses in specific categories.

4. Results and Discussion

4.1 Training and Validation Performance

The results indicate that the CNN model showed consistent convergence throughout the training, as depicted in the accuracy and loss trend throughout the 50 epochs. The training accuracy followed a pattern in which it improved significantly through the entire training epoch and would then appear to plateau after an initial increase. The validation accuracy showed a similar pattern but appeared to plateau after initially improving. This suggests a reasonable level of generalization.

This was confirmed with the trends in the training and validation loss, where the training loss decreased steadily and the validation loss plateaued - indicating there was no evidence of significant overfitting.

These patterns are shown in Figures 5 and 6, which show the loss curve and accuracy curve, respectively. The model was trained to highest capacity prior to the end of the epoch due to the early stopping and learning rate scheduling strategies employed.

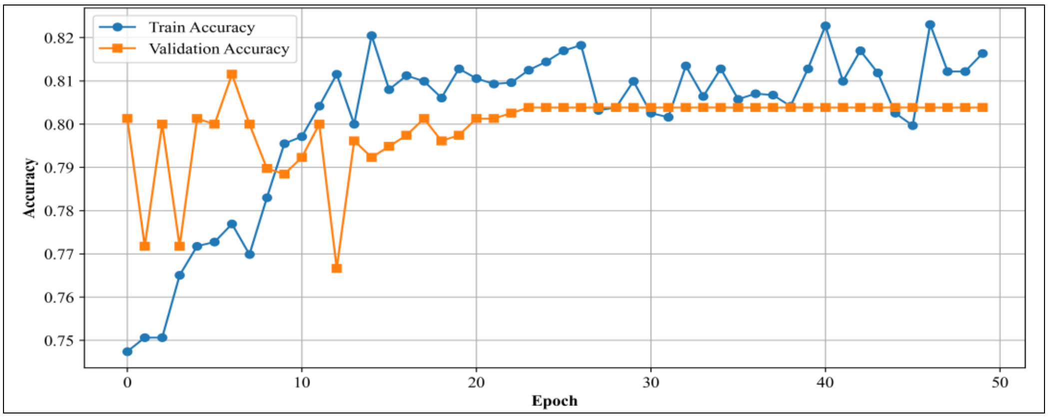

Fig 5: Training and validation accuracy across epochs.

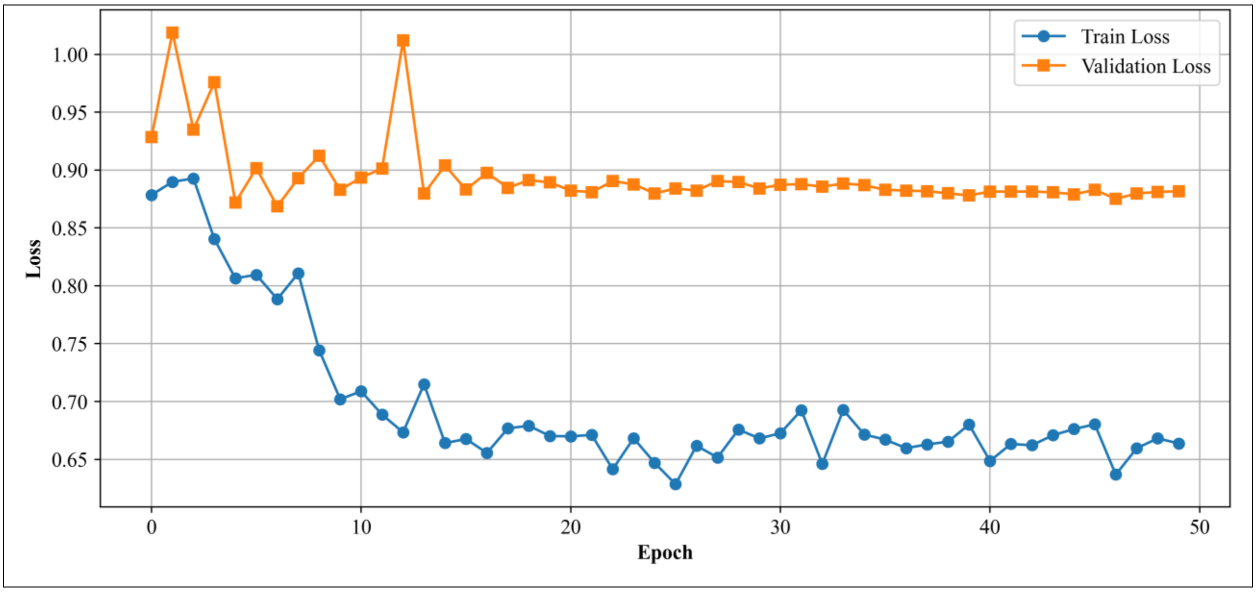

Fig 6: Training and validation loss across epochs.

4.2 Classification Results on the Test Set

The CNN model presented in this study achieved a test accuracy of 69.74% using the unseen dataset. Additionally, to general accuracy, a complete classification report was generated, providing precision, recall and F1-score for each of the 78 drug classes. These metrics provide additional insights into model performance, particularly during multiclass classification tasks due to the visual similarities between classes.

The macro-average F1-score and the weighted-average F1-score both reported 0.70, indicating consistent performance on both the dominating classes and less represented classes.

Some classes such as Azyth, Lucan-R, and Tamen had perfect or near-perfect F1-scores, whereas Rivotril and Renova classes had much lower F1-scores indicating these are the classes where the model struggles the most due to similarities in written names.

To help with interpretability and error analysis, Figure 7 shows the raw confusion matrix, while Figure 8 shows the confusion matrix in a normalized manner for ease of evaluation. Due to potential error clustering in certain classes, Figure 9 shows the top 10 most confused classes which highlights specific areas to focus on when improving the model.

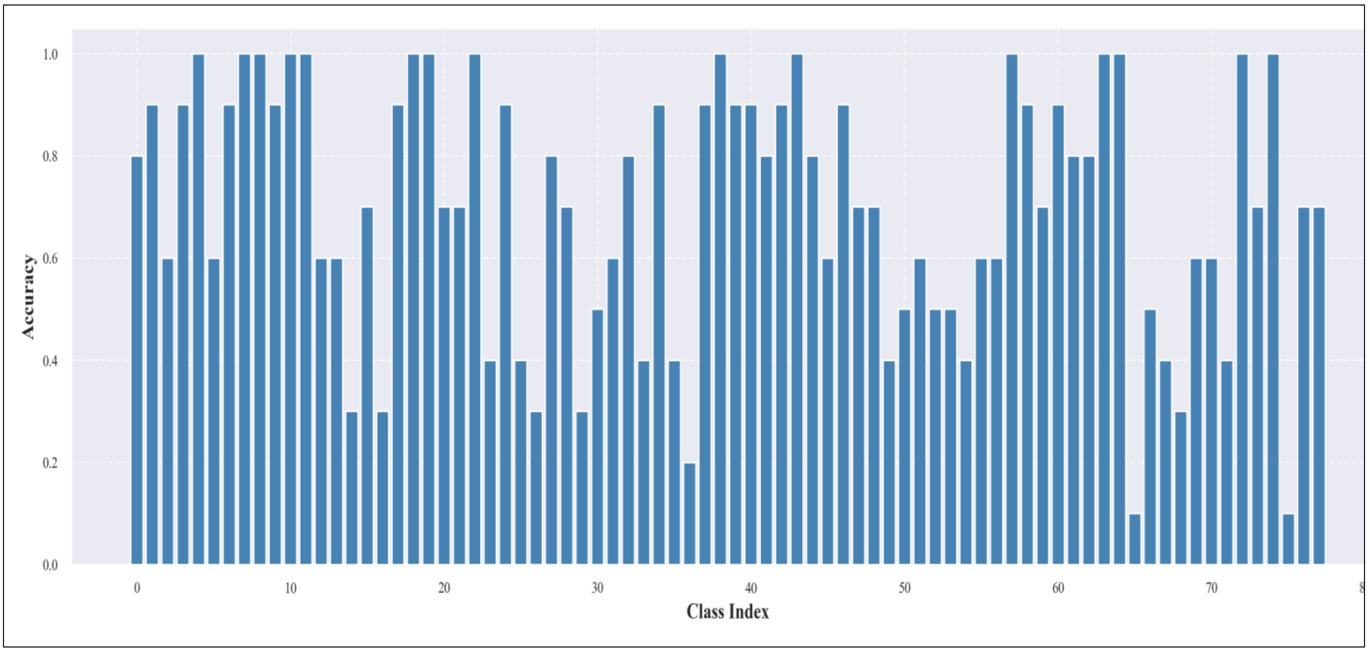

Fig 7: Per-Class Accuracy Across All 78 Drug Classes.

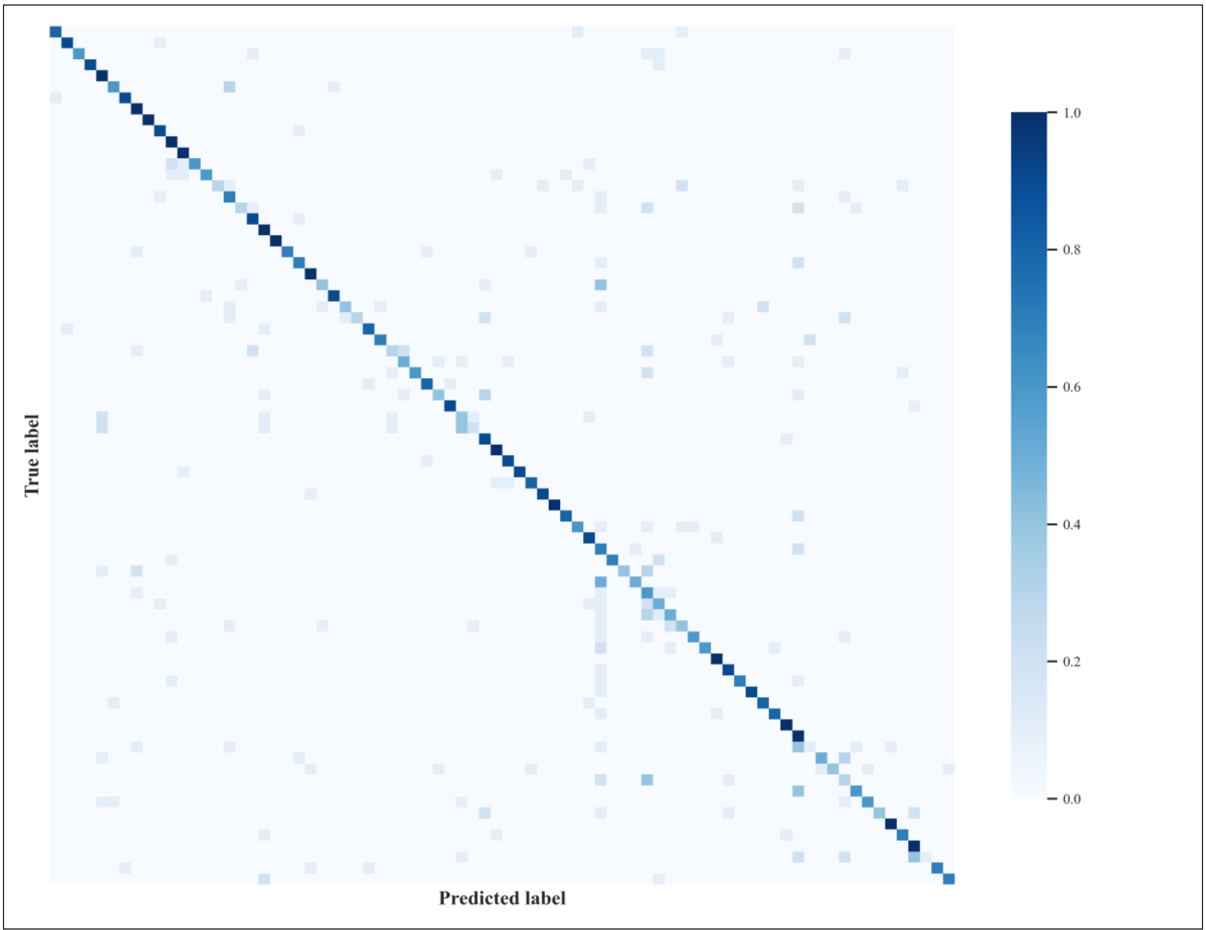

Fig 8. Normalized Confusion Matrix for Multi-Class Drug Name Classification.

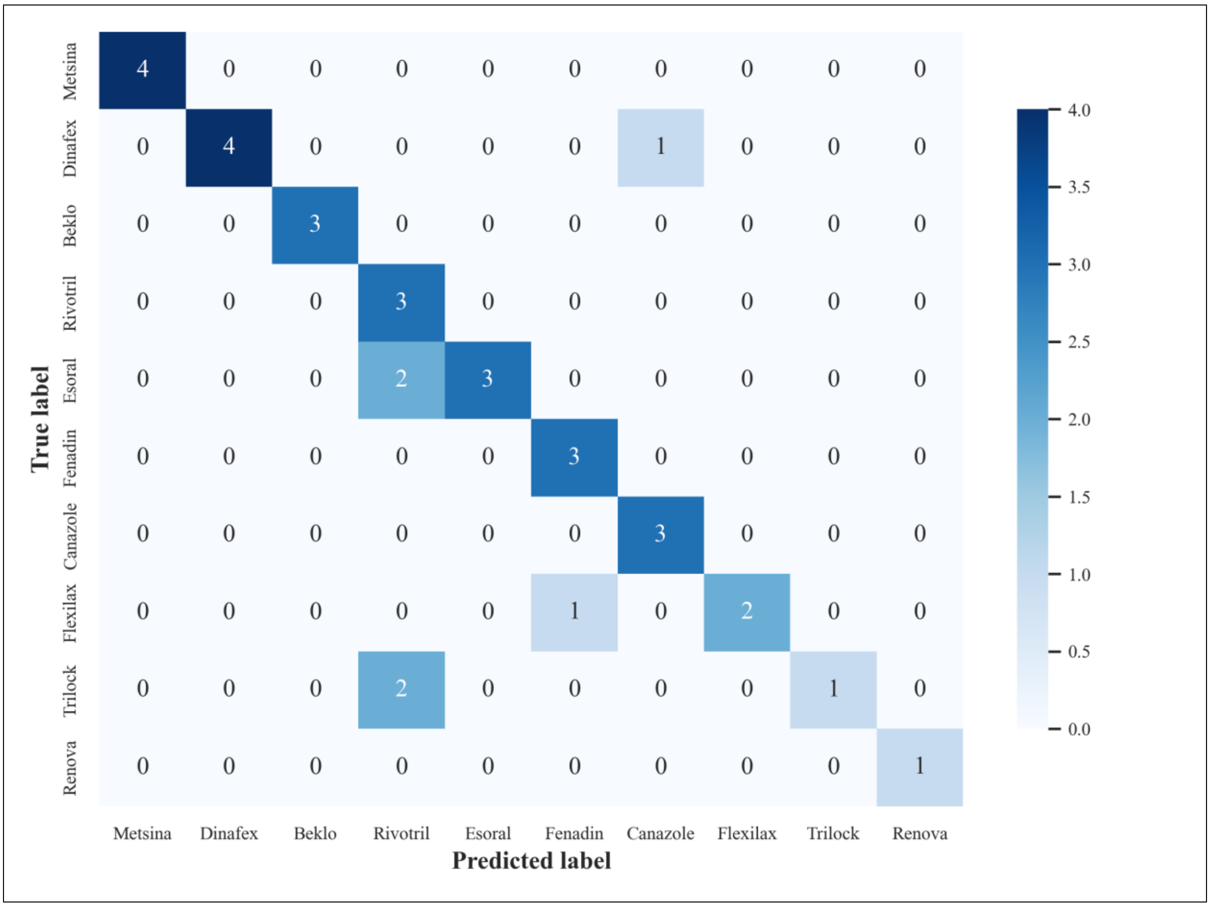

Fig 9: Confusion Matrix Highlighting the Top 10 Most Confused Drug Classes.

4.3 Visual Interpretation Using Grad-CAM

To increase interpretability of the CNN model's decisions, we applied Grad-CAM (Gradient-weighted Class Activation Mapping) technique to a sample of correctly classified and misclassified samples. The heatmaps illustrated the most contributory areas of the handwritten drug names of the CNN model's predictions. As shown in Figure 10, the CNN model consistently focused on individual character strokes and more identifiable lettering in correctly predicted samples (for example, Ace, Atrizin) while ensuring less informative lettering or misleading lettering in mislabeled samples (e.g. Axodin mislabeled as Bicozin).

Fig 10: Grad-CAM visualizations for selected handwritten drug names (correct and incorrect predictions).

4.4 Comparative Evaluation and Discussion

The performance of the proposed CNN-based model for the classification of handwritten drug names achieved a test accuracy of 69.74% with a macro- and weighted-average F1-scores of 0.70. The testing accuracy of our model is encouraging considering the difficulty of classifying 78 drug classes, which can significantly vary in style and is often unclear in handwritten forms.

This performance is like those achieved in other work in the handwritten prescription recognition domain. For example, Shahade *et al.* [27] used a CNN model for recognizing text in medical prescriptions and obtained 70% test accuracy, which is similar to the accuracy reported here. Their research shows the ability for CNNs to learn aspects of spatial relevance in even a noisy handwritten context.

In another publication, Brian Lobo *et al.* [37] employed a hybrid CNN-LSTM model to evaluate handwriting generated by healthcare professionals. In their publication, they found that their design yielded an 81.10% accuracy. Their architecture achieved a higher performance than our architecture; however, they focused on a smaller label set than this study and benefited from sequence modeling capabilities afforded by LSTM layers. Our effective CNN-only model, labeled CBRA, provides compelling performance for a larger class set, and achieves performance differences without temporal modeling [37].

Further, Sharma *et al.* [38] developed and reported DocAssist which utilized CNN-based algorithms to identify non-compound handwritten prescriptions and reported an 81% accuracy with their own CBRA experiment. While the model was effective, their study targeted a much broader outcome related to signature perception and legibility as opposed to multi-class identification on drug names.

In contrast with these studies, the present model is unique in terms of scale, with a much higher number of classes (78), and consequently offers a finer-grained analysis. Furthermore, the specific evaluation - confusion matrices (Figures 8 & 9), per class accuracy (Figure 7), and Grad-CAM heatmaps (Figure 10) respectively - provided considerable detail on performance weaknesses and potential improvements, or at least performance characteristics. Specifically, we clearly identified the classes "Azyth" and "Lucan-R" as having strong identification while the classes "Rivotril" and "Renova" suffered from high visual similarity, or vagueness in writing, respectively.

5. Conclusion

This research article reports on an effective deep learning model based on a CNN for classifying handwritten drug names, which represents a critical contribution to mitigating deficiencies in clarity and accuracy of medication prescriptions. Trained and evaluated on 78 drug classes, the CNN was able to achieve a test accuracy of 69.74% with macro- and weighted-F1 scores of 0.70, meaning that the model was able to generalize to classes that were visually different well. These improvements were bolstered with high-definition test plots, confusion matrices, and Grad-CAM visualizations to support the interpretation of the reasoning process by the model. The CNN-based classification framework offers a new approach to the digitization of medication prescriptions, supporting enhanced readability of handwritten drug names and efforts toward pharmacy automation and patient safety. In the context of the breadth and depth of more recent published work on healthcare handwriting classification, the model demonstrated good performance across a more extensive, granular class distribution.

Despite the benefits, there are limitations in this research. The dataset is relatively homogenous in terms of writing styles and image acquiring conditions such as paper quality and illumination. These homogeneity issues may impede generalizability to real-world applications. The model was also trained on grayscale only without considering contextual information (e.g. prescription layout and drug names shown together). While the CNN architecture was effective, it was still relatively simple architecture and did not use temporal modeling, such as RNNs of attention mechanisms, which could have discerned more detailed information in handwriting with more complexity. Finally, although stratified splitting was performed, there remained minor class imbalance that may have impacted performance of underrepresented classes of drugs.

Building upon these findings, future research could explore several enhancements:

- **Hybrid architectural designs:** Integrating LSTM layer(s) or transformer-based approaches (e.g., TrOCR) to better handle recognition of the complicated or sequential nature of handwriting.
- **Data augmentation:** Using more diverse, and more aggressive augmentations such as rotation, noise and blurring, to enhance robustness under real-world variability.
- **Multimodal input:** Using contextual cues, such as a prescription format (e.g., name of patient), or recognized text from OCR, that could possibly reduce ambiguity between visually similar drug names.
- **Transfer learning:** Using pre-trained vision models (e.g., ResNet, EfficientNet, or Vision Transformers, ViT), to expedite model training and improve accuracy.
- **Deployment and real-time testing:** Deploying the model in a real-world prescription-scanning systems to assess actual usability and inform on the potential for making improvements towards enhanced efficiency and reliability.

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