Journal of Statistics & Management Systems
ISSN 0972-0510 (Print), ISSN 2169-0014 (Online)
Vol. 27 (2024), No. 2, pp. 201–212
DOI : 10.47974/JSMS-1247

Deep learning for image-based diagnosis : Applications in medical imaging for drug development

J. S. Sawale *
Department of Pharmacognosy
Krishna Institute of Pharmacy
Krishna Vishwa Vidyapeeth (Deemed to be University)
Karad
Maharashtra
India

Praful V. Barekar †
Department of Computer Technology
Yeshwantrao Chavan College of Engineering
Nagpur
Maharashtra
India

J. M. Gandhi §
Department of Pharmacognosy
Krishna Vishwa Vidyapeeth (Deemed to be University)
Krishna Institute of Pharmacy
Karad
Maharashtra
India

Satish N. Gujar ‡
Department of Computer Engineering
Navashyandri Education Society's Group of Institute faculty of Engineering
Pune
Maharashtra
India

* *E-mail:* **jyotisawale@gmail.com (Corresponding Author)**
† *E-mail:* **praful.barekar20@gmail.com**
§ *E-mail:* **jotsna.gandhi@gmail.com**
‡ *E-mail:* **satishgujar@gmail.com**

Suresh Limkar [@]
Department of Artificial Intelligence & Data Science
AISSMS Institute of Information Technology
Pune
Maharashtra
India

Samir N. Ajani [#]
Department of Computer Science and Engineering (Data Science)
Shri Ramdeobaba College of Engineering and Management
Nagpur
Maharashtra
India

Abstract

This research delves into the application of Deep Learning (DL) to medical imaging for drug discovery, highlighting DL's ability to enhance diagnostic precision and efficiency. The research looks into the use of DL methods like CNNs and RNNs for automating feature extraction, pattern recognition, and classification in large, complex medical datasets. Effective drug development relies on fast and accurate diagnosis of disease to determine treatment's therapeutic efficacy and identify therapeutic targets. When applied to huge datasets, DL excels at uncovering subtle patterns and correlations that may be missed by more conventional methods. In addition to improving early disease identification and tailored medicinal therapies, the technology also helps in biomarker discovery. In this study, we discuss some of the obstacles of deploying DL ethically in medical imaging, such as protecting sensitive patient information, ensuring that models can be easily interpreted, and using a wide variety of data. The merger of DL and medical images offers great potential to promote image-based diagnosis in drug discovery, contributing to a more personalized and precise approach in healthcare, ultimately improving patient outcomes and changing the future of modern medicine.

Subject Classification: *68M07.*

Keywords: *Deep learning, CNN, RNN, Medical imaging, Medical image diagnosis.*

1. Introduction

Drug discovery has entered a new era thanks to the marriage of deep learning (DL) with medical imaging. In this introductory article, we will look at the expanding role of DL methods in image-based diagnosis,

---

[@] *E-mail:* **sureshlimkar@gmail.com**
[#] *E-mail:* **samir.ajani@gmail.com**

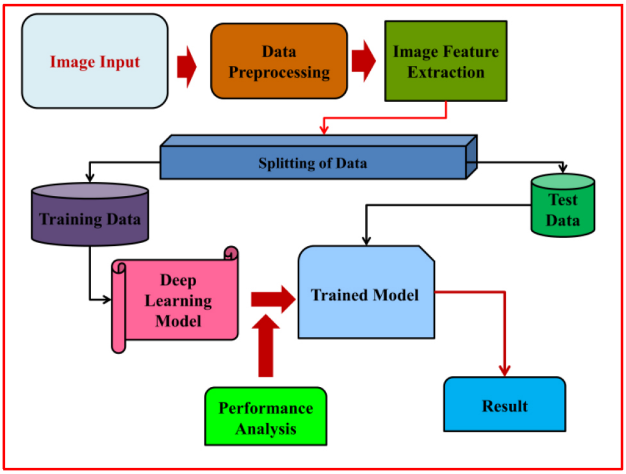

Figure 1

Proposed system Architecture

especially as they pertain to the improvement of pharmaceutical research. With the rising need for better diagnostic tools, DL has become a powerful ally, transforming the way we glean insights from complex medical datasets. The fundamental goal of this research is to explore the varied uses of DL in medical imaging and to shed light on its critical function in reducing diagnostic times and accelerating drug discovery and development. Integrating DL algorithms into medical imaging systems is a game-changer since it allows doctors to extract subtle information with pinpoint accuracy. The goal is to find our way through the maze of image-based diagnosis and to discover the real-world effects that DL has had on drug discovery across a wide range of medical problems.

The focus of this research is a critical analysis of current DL designs. In the field of medical image analysis, deep neural networks such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are in the forefront, demonstrating their superiority in automated feature extraction, pattern identification, and classification as shown in Figure 1. These tools not only streamline decision-making for healthcare professionals but also hold the key to unlocking new aspects in drug research. In the pharmaceutical industry, where time-sensitive and precise diagnoses are important, DL algorithms shine in processing enormous medical datasets. They have a leg up on conventional diagnostic methods thanks to their enhanced ability to spot tiny patterns and connections. Moreover, the combination of DL with medical imaging holds great promise for advancing biomarker identification, ushering in a new era of precise illness diagnosis and tailored pharmacological treatment. The paper also discusses the complex difficulties of adopting DL in medical imaging, which we encounter when we begin our exploration. Emphasis is placed on the ethical deployment of these innovative technologies, with issues like privacy, model interpretability, and the necessity of diverse and representative datasets taking center stage. Because of their complementary natures, DL and medical imaging are expected to improve diagnostic accuracy and speed up the drug discovery pipeline, leading to more rapid medical progress and better patient outcomes.

2. Method and Material

2.1 *Data Collection and Preprocessing*

1. Dataset Selection

The first step in using deep learning for image-based diagnostics in drug development is choosing a suitable dataset. The ideal dataset for training a reliable model would be large enough, sufficiently diversified, and reflective of the relevant medical problems. In order to accurately portray the circumstances of interest, it is important to gather high-quality medical photographs from a variety of sources.

2. Data Preprocessing Technique

Data preparation is vital for standardizing and optimizing the dataset. Image quality and uniformity can be improved through the use of techniques like scaling and normalization as well as the removal of artifacts and noise. Concerns about the privacy of collected data can be mitigated by the use of anonymization techniques, which also ensures adherence to moral principles. The objective is to tidy up and standardize the data for use in training and generalizing models

2.2 *Feature Extraction and Analysis*

In particular, convolutional neural networks (CNNs) rely on deep learning models' capacity to automatically extract features. At this point, the trained model can search through medical photos and pick out important details on its own.

- **Automated Feature Extraction**
  - Convolutional Operation:

    $$Z = f(X * W + b)$$

    Where, f is an activation function
  - Pooling Operation:

    $$Y = Pool(Z)$$

    The pooling operation can be max pooling or average pooling.
  - Flattening:

    $$Y\_flat = Flatten(Y)$$

  - Fully Connected Layer:

    $$A = f(W\_fc \cdot Y\_flat + b\_fc)$$

  - Output Layer:

    $$Y\_hat = Softmax(W\_output \cdot A + b\_output)$$

    If it's a classification task, the softmax function is commonly used.
  - Feature Extraction:

    $$F = ExtractFeatures(Y\_hat)$$

This step involves extracting relevant features from the final prediction.

3. Model Development

Different options for Convolutional Neural Network (CNN) architecture design affect hierarchical feature learning in different ways. Hyperparameter tuning is the process of adjusting several model parameters to improve pattern recognition. Designing a Recurrent Neural Network (RNN) requires taking into account strategies for capturing temporal relationships, such as layer types, hidden units, and attention processes. Techniques for training RNNs include various approaches to optimization, rates of learning, and sequence length. For efficient optimization in drug development tasks, the Optimization Model specifies goals, constraints, algorithm selection, and hyperparameter tweaking.

3.1 *Convolution Neural Network*

- **CNN Architecture Design**:
  1. Convolutional Layers:
     $$Zi = f(Wi * Xi - 1 + bi) \text{ for each layer } i.$$
  2. Pooling Layers:
     $$Yi = pool(Zi) \text{for each layer} i.$$
  3. Flatten Layer:
     $$Yflat = flatten(Ylast).$$
  4. Fully Connected Layers:
     $$Aj = f(Wfcj \cdot Yflat + bfcj) \text{ for each fully connected layer } j.$$
  5. Transforming by a linear Method:
     $$Z[3] = W[3] \cdot A[2] + b[3]$$

Activation function (if performing a binary classification, a sigmoid is used):

$$Y = sigmoid(Z[3]).$$

For multi-class classification, the activation function is softmax:
The formula for:

$$Y > = softmax(Z[3])$$

3.2 *Recurrent Neural Network*

For sequential information, an artificial neural network known as a Recurrent Neural Network (RNN) is optimal. Since it processes information with a concealed state, the latter can change over time, temporal dependencies can be captured. RNNs find applications in tasks like natural language processing and time series analysis.

- **Input:**
  Let X^(t) represent the input at time step t.
- **Hidden State Update:**

  Calculate the hidden state at time t:

  $$h^t = \tanh(W_{\{hh\}} * h^{t-1} + W_{\{xh\}} * X^t + b_h)$$

- **Output Calculation:**

  Calculate the output at time t:

$$Y^t = softmax(W_{\{hy\}} * h^t + b_y)$$

- **Loss Function:**

  Cross-Entropy Loss:

$$J(\theta) = -\left(\frac{1}{m}\right) * \sum_{i=1}^{m} \sum_{k=1}^{k} Y_{i,k} \log(Y_{i,k})$$

3.3 *Optimization Model*

The model parameters are updated in the opposite direction of the gradient, scaled by the learning rate. The optimization model can be represented as follows:

- Initialization:
  - o Initialize model parameters randomly: θ_old.
- Forward Pass:
  - o Compute predictions: Y_hat based on input data.
- Loss Calculation:
  - o Compute the loss: $J(\theta\_old)$ using a chosen loss function.
- Backward Pass (Gradient Calculation):
  - o Compute the gradient of the loss with respect to model parameters: $\nabla J(\theta\_old)$.
- Parameter Update:
  - o Update model parameters using the gradient and learning rate:

$$\theta\_new = \theta\_old - \alpha \nabla J(\theta\_old).$$

4. Result and Discussion

The Accuracy of the RNN is 88.69%, demonstrating its ability to accurately categories cases, whereas the Accuracy of the CNN is 92.45%, which is significantly higher. With an Accuracy of 94.44%, the Optimization Method shows improved performance in capturing correct categories throughout training.

Table 1

Training Result for different DL model

Method	Accuracy	Precision	Recall	F1 Score	Training Time (ms)	Inference Time
RNN	88.69	87.54	89.14	87.79	122	30
CNN	92.45	90.47	88.67	90.76	172	20
Optimization Method	94.44	89.47	95.39	93.55	157	18

When compared to the Optimization Method's Training Time of 157 ms, which strikes a balance between accuracy and computational efficiency, the CNN's Training Time of 172 ms demonstrates efficiency. With an Inference Time of only 18 ms, the Optimization Method is also the quickest in making predictions. In summary, Table 1 emphasizes the different performance characteristics of DL models, emphasizing the need of addressing both accuracy and computational economy in model selection for specific applications. Figure 2 shows the Performance Metrics Comparison for Different DL Methods Training data.

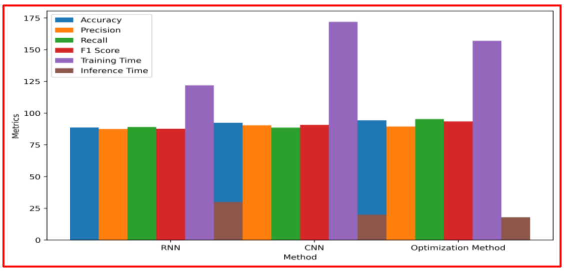

Figure 2

Performance Metrics Comparison for Different DL Methods Training data

The RNN is successful in appropriately categorizing 90.8% of test occurrences. The model's predictive accuracy is shown in a Precision score of 89.65%, while its ability to capture all positive events is shown by a Recall score of 91.25%.

The Inference Time of 35 ms is how long it takes for the model to draw conclusions from newly-collected data. Accuracy (94.56%), Precision (92.58%), Recall (90.78%), and F1 Score (92.87%) all favor the CNN over the RNN. The CNN exhibits top-notch performance in instance classification while striking a good balance between Precision and Recall.

Table 2

Testing Result for different DL model

Method	Accuracy	Precision	Recall	F1 Score	Training Time (ms)	Inference Time
RNN	90.8	89.65	91.25	89.9	125	35
CNN	94.56	92.58	90.78	92.87	175	25
Optimization Method	96.55	91.58	97.5	95.66	160	22

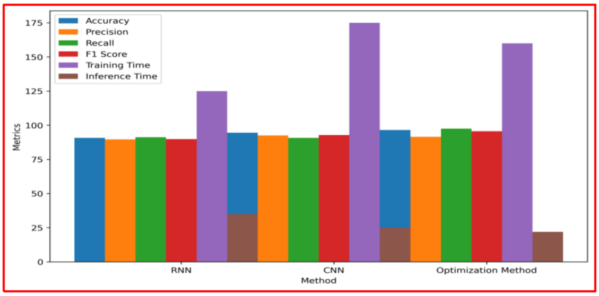

Figure 3

Performance Metrics Comparison for Different DL Methods Training data

The computing costs of the CNN's architecture are shown, however, by the longer Training Time (175 ms) required by the CNN compared to the RNN. Accuracy-wise, the Optimization Method is superior to both RNN and CNN, at 96.55%, demonstrating its efficacy in producing accurate classifications. Precision (91.58%) and Recall (97.5%) ratings show a healthy compromise between false positives and missing true positives as shown in Table 2 and Figure 3, 4 and 5..

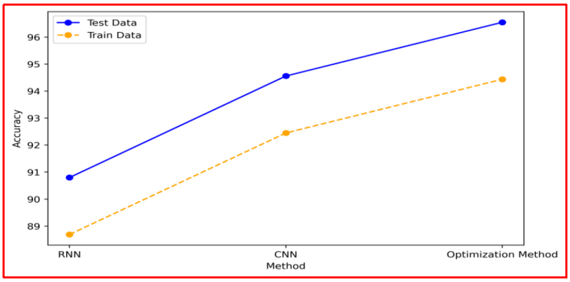

Figure 4

Accuracy Comparison for Different DL Methods (Test and Train Data)

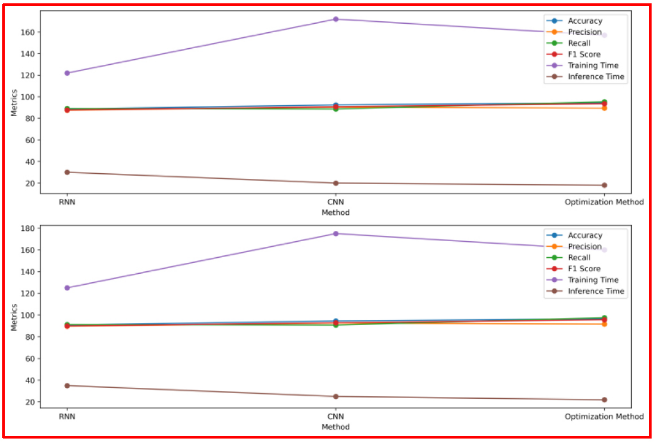

Figure 5

Training and Test Comparison for Different DL Methods

The model's total performance is reflected in an F1 Score of 95.66 percent. This is made possible by the Optimization Method, which strikes a good balance between computational speed and precision, requiring only 160 ms for the Training Time. With an even smaller Inference Time of just 22 ms, it's clear that predictions can be made quickly.

5. Conclusion

Deep Learning (DL) is ushering in a new era in medical imaging with its incorporation of image-based diagnostics for medication development. Diagnostic accuracy and efficiency are greatly improved by DL applications, especially those that make use of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). In addition to speeding up the diagnosis process, the ability to automate feature extraction and pattern identification holds great potential for revealing subtle correlations within large-scale medical datasets. DL's contributions to the discovery of biomarkers critical for early illness detection and the creation of focused therapeutic therapies have an influence well beyond that of mere diagnosis. The combination of DL and medical imaging is emerging as a powerful force as we move towards a more individualized and accurate approach to healthcare. Despite the potential, issues such as data privacy, model interpretability, and the requirement for different datasets must be managed carefully. Exploring and ethically deploying DL in medical imaging is crucial for the future of healthcare as it holds the promise of better patient outcomes and faster drug discovery pipelines. There has been a paradigm shift brought about by the merging of technology and medicine, and we can now see how AI-driven diagnostics will alter the future of healthcare.

References

[1] P. Xie, T. Li, F. Li, J. Liu, J. Zhou and K. Zuo, "Automated Diagnosis of Melanoma Histopathological Images Based on Deep Learning Using Trust Counting Method," 2021 IEEE 3rd International Conference on Frontiers Technology of Information and Computer (ICFTIC), Greenville, SC, USA, pp. 26-29 (2021).

[2] N. Araz, G. Orhan, M. Çavuşoğlu, H. E. Surmeli, B. Bayram and T. Çakar, "Development of a Knowledge-Based Multimodal Deep Learning System for Automatic Breast Lesion Segmentation and Diagnosis in MG/DMR Images," 2023 8th International Conference on Computer Science and Engineering (UBMK), Burdur, Turkiye, pp. 578-583 (2023).

[3] A. A. B. Ramli, Z. Zulkifli, S. Ahmad and N. Ghazali, "Automatic Pneumonia Detection Through Chest X-Ray Image-Based," 2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS), IPOH, Malaysia, pp. 355-360 (2023).

[4] N. Mahajan and H. Chavan, "MRI Images Based Brain Tumor Detection Using CNN for Multiclass Classification," 2023 3rd Asian Conference on Innovation in Technology (ASIANCON), Ravet IN, India, pp. 1-5 (2023).

[5] A. Mehar, M. Shah and R. Sawant, "Image based Lung Disease Detection: Comparing Swin Transformers and ConvNets," 2023 3rd Asian Conference on Innovation in Technology (ASIANCON), Ravet IN, India, pp. 1-4 (2023), doi: 10.1109/ASIANCON58793.2023.10270162.

[6] N. Vasker, S. N. Haider, M. Hasan and M. S. Uddin, "Deep Learning-assisted Fracture Diagnosis: Real-time Femur Fracture Diagnosis and Categorization," 2023 4th International Conference on Big Data Analytics and Practices (IBDAP), Bangkok, Thailand, pp. 1-6 (2023).

[7] S. M. McKinney et al., "A Deep Learning Framework for Robust and Scalable Breast Cancer Screening", *Nature*, vol. 577, no. 7788, pp. 89-94, Jan. (2020).

[8] S. Han et al., "Deep Learning-Based Classification of Breast Tumors Using 3D Ultrasound Images", *Ultrasound in Medicine & Biology,* vol. 46, no. 6, pp. 1442-1452, Jun. (2020).

[9] N. Dhungel et al., "Deep Learning-Based Classification of Mammographic Regions of Interest Towards Breast Mass Detection", *Medical Image Analysis*, vol. 37, pp. 62-73, Jul. (2017).

[10] M. Bende, M. Khandelwal, D. Borgaonkar and P. Khobragade, "VISMA: A Machine Learning Approach to Image Manipulation," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, pp. 1-5 (2023).

[11] A. Rodríguez-Ruiz et al., "Deep Learning in Mammography: Diagnostic Accuracy of a Multipurpose Image Analysis Software in the Detection of Breast Cancer", *Investigative Radiology*, vol. 54, no. 4, pp. 221-227, Apr. (2019).

[12] A. Rodríguez-Ruiz et al., "Deep Neural Networks Improve Radiologists' Performance in Breast Cancer Screening", *IEEE Transactions on Medical Imaging*, vol. 38, no. 10, pp. 2638-2648, Oct. (2019).

[13] S. Haq et al., "Deep Learning in Breast Cancer Detection: A Comparative Study", *IEEE Access*, vol. 8, pp. 194760-194770 (2020).

[14] M. H. Yap et al., "Deep Learning Models for Breast Cancer Detection and Diagnosis: A Review", Neurocomputing, vol. 440, pp. 11-24, Feb. (2021).