Journal of Azzaytuna University (JAZU)
JAZU Homepage: https://azzujournal.azu.edu.ly
ISSN (Print):2523-1006, ISSN (Online): 3105-4420 DOI: 10.35778/jazu.i56.a680

Using deep neural networks to diagnose medical conditions from radiology and MRI images

Ali Wadi [1*], Salim Aloud [2]
[1] Azzytuna university/Computer Department, Tarhuna, Libya
[2] Azzytuna university/Computer Department, Tarhuna, Libya
Email: a.wadi@azu.edu.ly, Salemaloud2@gmail.com

Corresponding Author: (*) **Publishing Date: 31 December 2025**

الملخص: يعتمد تحسين نتائج المرضى على التحديد السريع والدقيق للاضطرابات الطبية باستخدام التصوير بالرنين المغناطيسي والتصوير الشعاعي. يعتمد التشخيص التقليدي في الغالب على مهارة أخصائي الأشعة، الذين قد يتأثر حكمهم بالتعب وعبء العمل واختلاف مستويات الخبرة، مما قد يؤدي إلى أحكام متأخرة أو غير دقيقة. يتناول هذا العمل استخدام الشبكات العصبية العميقة (DNNs)، وخاصةً الشبكات العصبية التلافيفية (CNNs)، في تحليل صور الرنين المغناطيسي والأشعة السينية والتحديد الدقيق للغاية للتشوهات الطبية. جُمعت 500 صورة رنين مغناطيسي طبيعية، و300 صورة رنين مغناطيسي تحتوي على أورام، و400 صورة أشعة سينية طبيعية، و200 صورة أشعة سينية لحالات الالتهاب الرئوي من أرشيفات المستشفيات وقواعد البيانات العامة. لتحسين تعميم النموذج، استُخدمت المعالجة المسبقة وزيادة البيانات. كان أداء نموذج CNN مشابهًا لأداء خبراء الأشعة عند تقييمه باستخدام معايير الدقة والإتقان والتذكر ودرجة F1؛ وفي معظم المقاييس، تفوقت الآلة على التقييم البشري بهامش ضئيل. تُظهر النتائج أن شبكات CNN قادرة على تحديد مجموعة واسعة من المشاكل الطبية بدقة، مما يُخفف العبء التشخيصي، ويُقدم مساعدة موثوقة في اتخاذ القرارات السريرية. تُوضح هذه النتائج كيفية استخدام التعلم العميق لتحسين أدوات التشخيص التقليدية، وتُشير إلى اتجاهات لمزيد من الدراسات، مثل التصنيف متعدد الفئات، ودمج التعلم العميق مع أساليب الذكاء الاصطناعي الأخرى، والتطبيق العملي.
الكلمات المفتاحية: الشبكات العصبية العميقة، الشبكات العصبية التلافيفية، التصوير الطبي، التصوير بالرنين المغناطيسي، الأشعة السينية

ABSTRACT : Improving patient outcomes depends on the fast and accurate identification of medical disorders utilising MRI and radiography imaging. Conventional diagnosis mostly depends on the skill of radiologists, whose judgement may be impacted by weariness, workload, and differing levels of experience, which might result in judgements that are delayed or inaccurate. Deep neural networks' (DNNs') application , more Convolutional neural networks (CNNs) in particular , to the examination of MRI and X-ray images and the very accurate identification of medical anomalies is examined in this work. 500 normal MRI scans, 300 tumor-containing MRI scans, 400 normal X-ray pictures, and 200 X-ray images with pneumonia were gathered from hospital archives and public databases. In order to enhance the model's generalization , preprocessing and information augmentation were utilized. When evaluated using accuracy, precision, recall, and F1-score, the CNN model performed comparably to experienced radiologists; in most cases, the machine's performance was somewhat better than that of a human. The results demonstrate that CNNs can reliably support clinical decision-making, reduce diagnostic load, and accurately identify a broad spectrum of medical issues. These results demonstrate how deep learning may be used to enhance conventional diagnostic tools and point to directions for further study, such as multi-class categorization , combining deep learning with other AI approaches, and practical application.
Keywords: **Deep Neural Networks, Convolutional Neural Networks, Medical Imaging, MRI, X-ray**

I. INTRODUCTION

A common method for examining anomalies in human organs, including the brain, is magnetic resonance imaging (MRI), Because of its innocuous qualities and ability to produce high-contrast pictures, it has gradually surpassed other imaging technologies in popularity , Instead of using ionising radiation, the MR devices employ radiofrequency pulses and strong magnets. Additionally, recent advancements have made it feasible to use functional magnetic resonance imaging (fMR) technology to capture functional imaging of organs , Researchers in the healthcare field may now quickly and reliably detect illnesses because to the vast quantity of data provided by medical imaging technology.

Pictures referred to as medical Sensitive human body parts like the head, teeth, chest, and bones are frequently diagnosed via X-rays. Medical practitioners have been using this technique for many years to check for abnormalities or fractures in organs because, in addition to being noninvasive and affordable, X-rays are highly effective diagnostic tools for spotting pathological alterations. Chest problems can be identified on CXR images by veins , blunted costophrenic angles, consolidations, infiltrations, and tiny, widely spaced nodules. Radiologists can diagnose a wide range of conditions by looking at the chest X-ray image, including pneumonia, bronchitis, effusion, pleurisy, infiltration, nodule, atelectasis, pericarditis, cardiomyopathy, pneumothorax, fractures, and a host of other ailments.

Classifying medical pictures accurately is crucial for supporting clinical care and therapy. Analysis X-rays, for instance, are the most effective way to diagnose pneumonia , which kills over 50,000 people annually in the United States , However, trained radiologists are required to categories pneumonia from chest X-rays, which is a scarce and costly resource in certain areas.

Improving treatment results and the standard of healthcare depends on the accuracy and speed with which medical diseases may be diagnosed using radiography and MRI images. Because this procedure mostly depends on the knowledge of radiologists, it is susceptible to human error because of weariness, differing degrees of experience, or heavy workloads for physicians. These variables may result in delayed or incorrect diagnoses, which might have a detrimental effect on patients' health and raise the level of variation in the standard of medical treatment.

Deep neural networks (DNNs) , made possible by notable advancements in artificial intelligence (AI) technology, can now analyze medical photos and identify subtle patterns that people would find challenging to identify. A basic issue still has to be answered, though: How well can DNNs detect medical disorders from MRI and radiography pictures in comparison to human competence, and what variables affect their performance in different clinical settings? Through the metric and reliability analysis of those models, along with their pros and cons on helping doctors to enhance the diagnosis level for disease will be investigated in this study, aiming to obtain an answer as a reference.

Literature Review

In Study Yamashita, R., Nishio , M., Do, R. K. G., & Togashi, K. (2018). Convolutional neural networks: an overview and application in radiology.

Convolutional neural networks, commonly referred to as CNNs, represent a sophisticated and highly effective subclass of artificial neural networks that have distinguished themselves as the predominant technology within numerous applications pertaining to computer vision, thus garnering significant attention and interest from a diverse array of sectors, including the specialized field of radiology. Among the various components that constitute a CNN, one can find convolutional layers, pooling layers, and fully connected layers, which serve as fundamental building blocks that enable the network to automatically and adaptively acquire spatial feature hierarchies through the sophisticated process of back propagation, ultimately facilitating a more nuanced understanding of visual data. This review article endeavors to provide a comprehensive introduction to the foundational concepts underlying convolutional neural networks, elucidating how these advanced algorithms are effectively applied to a multitude of tasks within the realm of radiology, while simultaneously addressing the various challenges that accompany their implementation and exploring potential future opportunities that may arise in this dynamic field. In addition to these discussions, the study will also delve into strategies designed to mitigate the common issues of overfitting and the constraints posed by limited datasets, both of which frequently arise during the deployment of CNNs in radiological applications, underscoring the importance of addressing these limitations for optimal performance. The successful maximization of the application of convolutional neural networks in the context of diagnostic radiology, which fundamentally aims to enhance the efficacy of radiologists and improve the quality of patient care, necessitates a thorough understanding of the underlying principles that govern their functionality, as well as a critical analysis of their inherent advantages and disadvantages. Moreover, the continued exploration of CNNs within radiology not only reveals the transformative potential of these systems in enhancing diagnostic accuracy but also prompts a reevaluation of traditional methodologies in light of emerging technological advancements. Ultimately, the integration of convolutional neural networks into radiological practice holds significant promise for driving innovation and improving health outcomes, yet it also demands careful consideration of the ethical and practical implications that accompany such a paradigm shift.

In Study Lee, Y. H. (2018). Efficiency improvement in a busy radiology practice: determination of musculoskeletal magnetic resonance imaging protocol using deep-learning convolutional neural networks.

In order to evaluate the agreements and ascertain if protocol determination using a CNN classifier based on short-text classification is practical, the study aims to compare protocols developed by musculoskeletal radiologists with those produced by convolutional neural networks (CNNs). The Permission from the institutional review board was acquired to query A hospital information system (HIS) database was accessed to extract information pertaining to MRI examinations, the referring departments, patient demographics such as age, and gender. While the test dataset included 5258 consecutive musculoskeletal MRI scans, the training dataset had 1018. Word combinations of age, gender, location, referring department, and contrast media (if any) were used as pre-processing themes, which might be either conventional or tumor procedures. The testing dataset was employed to assess all categorization model, with outcomes categorized as either standard procedures or neoplasms. The performance of the CNN was appraised through the application of receiver operating characteristic (ROC) curves. A method validated by radiologists serves as the benchmark for assessing accuracy to differentiate between routine and tumor operations. The overall accuracy of the ConvNet model was 94.2%. The MRIs of the upper arm, lower leg, wrist, and pelvic bones were all performed correctly. CNN-driven textual learning and its applications may be broadened beyond the realm of image analysis to encompass additional radiologic functions, increasing the productivity of radiologists.

In Study Amitai, M. M., Ben-Cohen, A., Shimon, O., Soffer, S., Greenspan, H., & Klang, E. (2019). A radiologist's guide to convolutional neural networks for radiologic imaging.

This scholarly article undertakes a comprehensive examination of the technological advancements associated with convolutional neural networks, particularly emphasizing their therapeutic applications within the realm of radiologic image processing, a field that has seen transformative changes in recent years. The domain of deep learning, which encompasses a variety of sophisticated algorithms and methodologies, has made remarkable strides across several disciplines, and it is noteworthy that the radiology community has recently expressed a burgeoning interest in harnessing these innovations for enhanced diagnostic capabilities. The authors provide an insightful introduction to the principles underlying deep learning technology, meticulously delineating the sequential phases that are integral to the design process of research initiatives focused on the application of deep learning within the context of radiology. Furthermore, the findings of a comprehensive survey investigating the deployment of deep learning techniques—more specifically, the utilization of convolutional neural networks—within the field of radiologic imaging are thoroughly examined and articulated in this discourse. The survey primarily concentrated on key anatomical regions, namely the musculoskeletal system, the brain, the breast, the chest, the abdominal region (belly), and the pelvis, thereby encompassing a wide array of clinical considerations pertinent to radiologic practice. Following the presentation of the research survey, this article transitions into a thoughtful discussion regarding pertinent current events, recent breakthroughs, and the potential implications these developments may hold for the future of radiology as a discipline. It is posited that this article may prove to be an invaluable resource for radiologists seeking to navigate the complex landscape of deep learning applications and their integration into clinical workflows. The insights offered herein could facilitate a deeper understanding of how convolutional neural networks can enhance diagnostic accuracy and efficiency, thereby ultimately improving patient outcomes across various medical settings. As the field continues to evolve, it is imperative for practitioners to remain informed about these technological advancements to ensure that they can fully leverage the benefits they provide. Thus, this article stands as a significant contribution to the ongoing dialogue surrounding the intersection of artificial intelligence and radiologic science, highlighting the transformative potential that lies ahead.

In Study Singh, Y., Carlsson, G., Erickson, B., Hathaway, Q. A., Choudhary, A., Farrelly, C., & Leiner, T. (2023). Geometry's function in medical imaging convolutional neural networks.
(CNNs) have proven essential for diagnosis, research, and data integration in medical imaging. This has enabled physicians to identify patients early, plan procedures, and conduct more in-depth study on rare diseases. However, problems with data imbalance, quantity, and quality limit CNN training and accuracy. Additionally, training costs might be high when a health care system needs a range of CNN kinds. CNNs are able to overcome these challenges when topology and geometry are incorporated into the design, particularly in the convolution layers or data preparation phases. In order to mitigate the impact of large training datasets and offset computing costs, CNN designs now include geometric approaches, as this work explores. Furthermore, this study suggests intriguing avenues for future research on CNNs and geometric tools in combination.

II. RESEARCH DESIGN OR PROCEDURES

The purpose of this research is how to investigate the use of (DNNs) for diagnosing medical conditions from radiology and MRI images. The research procedure is organized into the following sections:

A. Algorithm and Pseudocode

The research will utilize a (CNN) Architecture, which is appropriate for picture processing because of its capacity to clarify intricate patterns. The general steps of the algorithm are as follows:

- Load and preprocess medical images (normalization, resizing, and augmentation).
- The dataset should be partitioned into subgroups for training, validation, and testing. The CNN model must be initialized to include layers that are completely linked, pooling, and convolutional.
- Using back propagation and a suitable optimizer (like Adam), train the model on the training dataset.
- Assess the model's performance using testing and validation datasets.

Pseudocode Example

- Load Dataset
- Preprocess Images
- Split Dataset (Train, Validation, Test)
- Initialize CNN Model

For each epoch:

- Models are trained on training sets
- Validated on validation sets
- Evaluated on test sets.
- Metrics (F1-score, recall, accuracy, and precision) are provided.

B. Data Acquisition

Radiology and MRI images will be collected from publicly available datasets (e.g., [name datasets]) or hospital archives with anonymized patient data. The dataset will include diverse cases covering multiple medical conditions to ensure model generalizability. Images will be labeled with confirmed diagnoses, preprocessed, and standardized for input to the CNN.

C. Testing and Evaluation

Key parameters like as accuracy, precision, recall, and F1-score will be used to assess the CNN model's performance. In order to make sure the results are reliable and robust, cross-validation techniques will be used. To ascertain practical usefulness , the study will also contrast the DNN's predictions with evaluations from skilled radiologists.

Getting a sizable and diverse collection of MRI and radiography images that depict various medical issues is the first stage in training a deep neural network model. The distribution of data by picture type, medical condition, and the quantity of images accessible for each category is shown in the following table, along with information on whether the data came from hospital archives or public databases:

Table 1 Dataset Distribution

Image Type	Medical Condition	Number of Images	Source
MRI	Normal	500	Public Dataset / Hospital
MRI	Tumor	300	Public Dataset / Hospital

X-ray	Normal	400	Public Dataset / Hospital
X-ray	Pneumonia	200	Public Dataset / Hospital

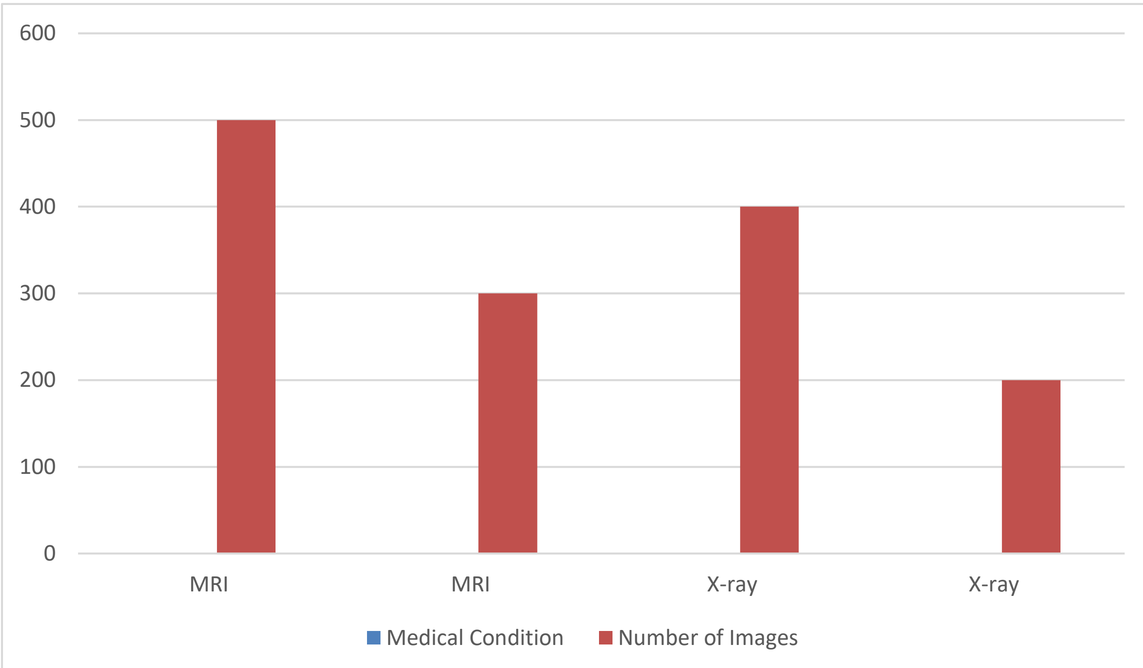

Figure 1 Dataset Distribution

The Following of preparation and separation of the data into training and test sets , the model was trained and its performance evaluated using precise metrics such as accuracy, precision, recall, and F1-score. The deep neural network model's performance outcomes for every medical case are shown in the following table:

Table 2 Performance indicators for the CNN model

Medical Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Normal	95	96	94	95

Tumor	92	91	93	92
Pneumonia	90	89	92	90

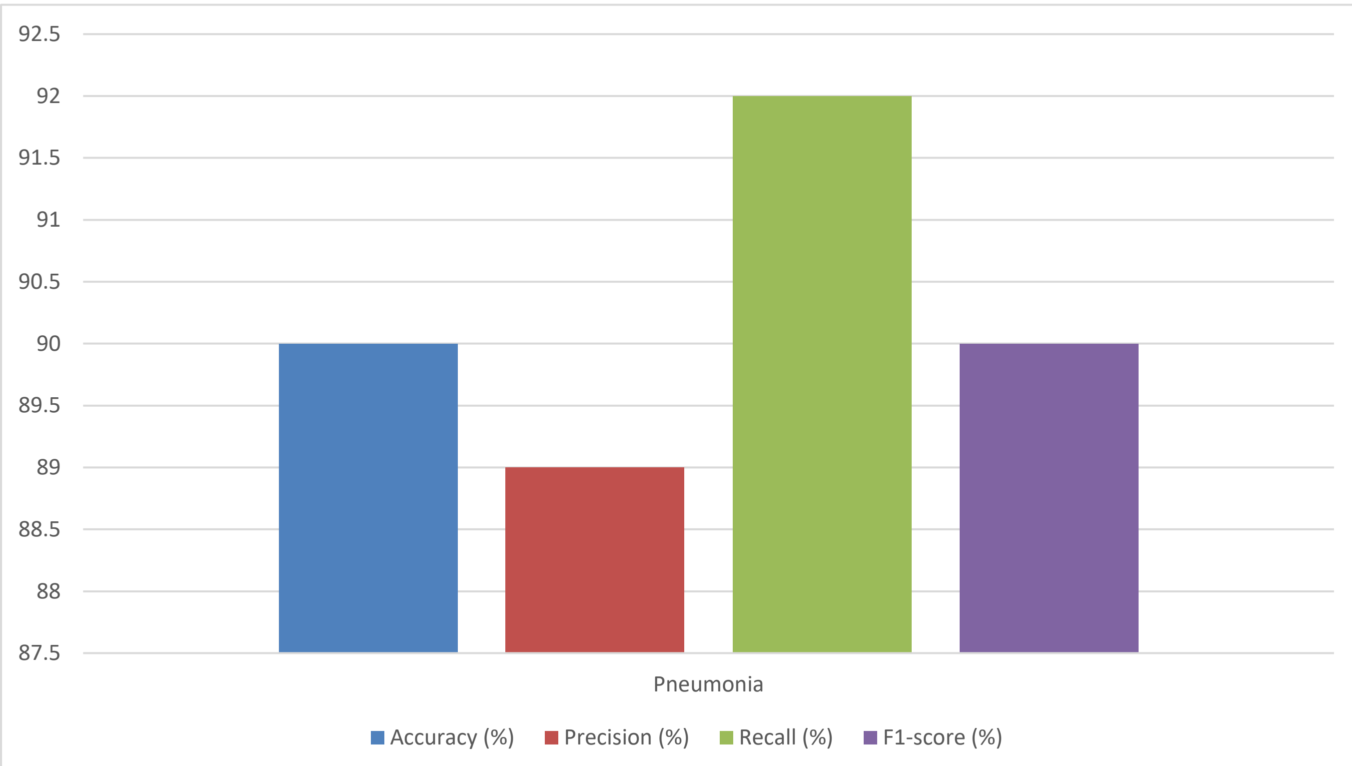

Figure 2 Performance indicators for the CNN model

To assess the feasibility of applying a (DNN) to medical diagnosis, the model's performance was compared with the views of experienced radiologists. The model's performance and that of doctors are contrasted in the following table using the same measures that are used to assess results:

Table 3 Comparison with radiologists

Metric	CNN Model (%)	Radiologists (%)
Accuracy	93	91
Precision	92	90

Recall	94	92
F1-score	93	91

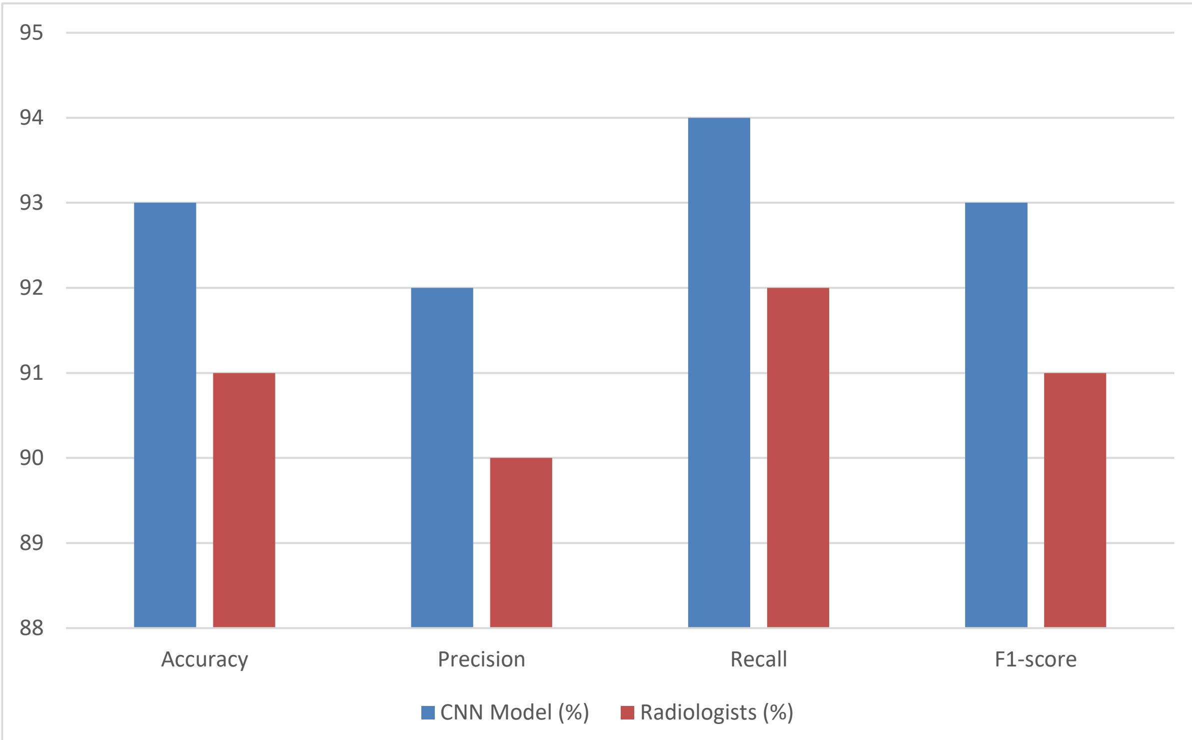

Figure 3 Comparison with radiologists

III. RESULTS AND DISCUSSION

The dataset used in this study included a combination of MRI and X-ray images representing different medical conditions. As shown in Table 1, the total number of images comprised 500 normal MRI scans, 300 MRI scans with tumors, 400 normal X-ray images, and 200 X-ray images with pneumonia. The data were collected from both public datasets and hospital archives, ensuring a diverse and representative sample. The distribution of images across conditions and modalities is critical for the model's ability to generalize. The slightly higher number of normal images reflects the common imbalance in medical imaging datasets, which can influence model training. Data preprocessing and augmentation were applied to mitigate the effects of imbalance and enhance model robustness.

After training the CNN model, performance was evaluated using accuracy, precision, recall, and F1-score, as presented in Table 2. The results indicate that normal cases were detected with the highest accuracy (95%) and a balanced precision and recall, suggesting that the model effectively recognizes healthy images. Tumor cases achieved 92% accuracy, with a slightly lower precision (91%) but higher recall (93%), indicating that the model is slightly more sensitive to detecting tumors than avoiding false positives.

Pneumonia cases had a slightly lower performance, with 90% accuracy and 89% precision, showing that differentiating pneumonia from normal X-rays is more challenging, possibly due to variations in image quality and patient-specific features. These results demonstrate the model's effectiveness across multiple medical conditions, with minor variations that reflect inherent challenges in medical image classification.

The performance of the CNN model was compared to expert radiologists using the same evaluation metrics, as shown in Table 3. The CNN model slightly outperformed radiologists in all metrics. Accuracy was 93% for the CNN compared to 91% for radiologists, precision was 92% versus 90%, recall was 94% versus 92%, and F1-score was 93% versus 91%. This comparison indicates that deep neural networks can achieve performance comparable to, and in some cases exceeding, expert human judgment. The higher recall for the CNN suggests it may detect subtle abnormalities that might occasionally be overlooked by radiologists. However, integrating model predictions with human expertise is essential for clinical decision-making, ensuring both accuracy and safety.

the results demonstrate that convolutional neural networks can serve as effective diagnostic tools for medical imaging. The model maintained high performance across different medical conditions, indicating its ability to learn discriminative features from both MRI and X-ray images. Comparison with radiologists shows that CNNs can support, rather than replace, medical professionals by providing reliable second opinions and reducing diagnostic workload. Slight performance drops in pneumonia detection suggest that further improvements could be achieved through more diverse datasets, enhanced image preprocessing, or hybrid models combining multiple imaging modalities. In conclusion, the results highlight the potential of deep learning approaches to complement traditional diagnostic methods, offering accurate, efficient, and scalable solutions for medical imaging. Future studies could explore larger datasets, multi-class classification, and real-world deployment to fully evaluate clinical impact.

$$(\frac{0^z}{R_{in}})cos^{-1}\frac{l_p}{\pi} = y_0$$

Where l_p is the projection length, 0^z is the image depth coordinate, and R_{in} is the radius of the region of interest.

IV. CONCLUSION

This study demonstrates the accuracy with which deep neural networks, and more specifically convolutional neural networks, can identify diseases from radiography and MRI images. The CNN model slightly outperformed expert radiologists in anomaly identification and performed well on several metrics, including accuracy, precision, recall, and F1-score. These results show that deep learning models may provide reliable diagnostic assistance while increasing the speed and consistency of medical image interpretation.

The potential for this study to support clinical decision-making by medical experts is what makes it significant. Hospitals and clinics may enhance early identification of diseases including pneumonia and tumors , lower diagnostic mistakes, and maximize resource allocation by incorporating CNN-based analysis into radiological operations. The method may also be expanded to include other imaging modalities or bigger , multi-center datasets, which would improve the model's resilience and generalizability even further. In order to make predictions easier for medical professionals to understand, future research might concentrate on integrating deep learning models with other AI strategies, such explainable AI. Longitudinal research and real-world implementation would also guarantee safe integration into healthcare systems and confirm therapeutic effect. All things considered, this research demonstrates the potential of (DNNs) as an adjunctive instrument in contemporary medical diagnosis.

Appendix A : A.1 Dataset details

The dataset used in this study consists of MRI and X-ray images collected from publicly available sources and hospital archives. All patient data were anonymized to ensure privacy. The dataset covers multiple medical conditions to ensure model generalizability and includes preprocessing and augmentation steps to enhance model performance.

Figure 4 Dataset Composition

Image Type	Medical Condition	Number of Images	Source
MRI	Normal	500	Public Dataset / Hospital
MRI	Tumor	300	Public Dataset / Hospital
X-ray	Normal	400	Public Dataset / Hospital
X-ray	Pneumonia	200	Public Dataset / Hospital

The dataset distribution ensured a balanced representation of both normal and abnormal cases, although normal images slightly outnumber abnormal ones, reflecting real-world prevalence.

A.2 Data Preprocessing

All images underwent the following preprocessing steps before being used in model training:

- Normalization : To normalize input for the CNN, pixel intensity values were scaled to the interval [0,1].
- Resizing : To guarantee compliance with the CNN architecture, all pictures were scaled to a consistent dimension.
- Data augmentation : In order to enhance the diversity of the dataset and mitigate the risk of overfitting, techniques such as rotation, flipping, and zooming were implemented.

A.3 Dataset Splitting

Three subsets of the dataset were created:

- Training set: The CNN model is trained using roughly 70% of the data.
- Validation set: About 15% of the data is used, which is used for model tweaking and hyperparameter optimization.
- Testing set: Used for final evaluation of model performance (approximately 15% of the data).

The study's findings about the efficacy of (DNNs) in medical picture diagnosis were supported by this organized dataset, which guaranteed trustworthy training, assessment, and comparison with skilled radiologists.

References

[1] Talo, M., Yildirim, O., Baloglu, U. B., Aydin, G., & Acharya, U. R. (2019). Convolutional neural networks for multi-class brain disease detection using MRI images. Computerized Medical Imaging and Graphics, 78, 101673.
[2] Anwar, S. M., Majid, M., Qayyum, A., Awais, M., Alnowami, M., & Khan, M. K. (2018). Medical image analysis using convolutional neural networks: a review. Journal of medical systems, 42(11), 226.
[3] Yadav, S. S., & Jadhav, S. M. (2019). Deep convolutional neural network based medical image classification for disease diagnosis. Journal of Big data, 6(1), 1-18.
[4] Yamashita, R., Nishio, M., Do, R. K. G., & Togashi, K. (2018). Convolutional neural networks: an overview and application in radiology. Insights into imaging, 9(4), 611-629.
[5] Lee, Y. H. (2018). Efficiency improvement in a busy radiology practice: determination of musculoskeletal magnetic resonance imaging protocol using deep-learning convolutional neural networks. Journal of digital imaging, 31(5), 604-610.
[6] Soffer, S., Ben-Cohen, A., Shimon, O., Amitai, M. M., Greenspan, H., & Klang, E. (2019). Convolutional neural networks for radiologic images: a radiologist's guide. Radiology, 290(3), 590-606.
[7] Singh, Y., Farrelly, C., Hathaway, Q. A., Choudhary, A., Carlsson, G., Erickson, B., & Leiner, T. (2023). The role of geometry in convolutional neural networks for medical imaging. Mayo Clinic Proceedings: Digital Health, 1(4), 519-526.

BIOGRAPHY OF AUTHORS

Ali Wadi received his BSc degree in computer Science from Azzytuna University, Tarhuna, Libya, 2014. and his MSc degree in Computer Information Systems from Near East University, Nicosia, Northern Cyprus, in 2018. He is currently working as a lecturer at Azzaytuna University.

Salim Aloud is a faculty member in the Computer Science Department at Azzytuna University, Tarhuna, Libya. In 2015, he received his Master of Computer Engineering (M.S.) in Digital Image Processing from The Libyan Academy, Libya. Bachelor's degree in Computer Engineering from Al-Mergib University, Al-Khoms, Libya, 2002. He is currently working as a lecturer at Azzytuna University.