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Elevating X-ray Image Classification Performance with wavelet Fusion and deep Learning

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A B S T R A C T

Medical imaging has seen a significant advancement in recent years, with the introduction of multi-spectral X-ray imaging being one notable development. However, traditional image fusion methods such as weighted averaging or maximum intensity projection may not be sufficient to address the complexities of X-ray images. In response, a new deep learning-based multi-spectral X-ray image fusion method has been developed. This method utilizes Convolutional Neural Networks(CNNs) utilizes deep learning algorithms to combine multiple images obtained from different X-ray energy levels into a single image with higher resolution and improve quality. The problem statement highlights the limitations of traditional X-ray imaging methods and the challenges in developing an effective image fusion method. The proposed approach's contribution is a step towards improving the quality and accuracy of medical imaging, leading to better patient outcomes and more efficient healthcare practices. The provided results indicate that the proposed model achieved an accuracy of 95% on the training data and 90% on the test data, with room for improvement. The limitation of the dataset and the algorithm used for classification are discussed as potential reasons for not achieving higher accuracy. Further research is required to develop specialized deep learning models for X-ray image fusion and explore other algorithms and techniques to address the challenges related to the dataset and the algorithm used for classification.

1. Introduction

Medical imaging technology has progressed remarkably recently, particularly with the development of multi-spectral X-ray imaging. This method captures a series of images of the same objects at different X-ray energy levels to provide a more comprehensive view. A new work done in this field is the work on deep learning based multi spectral X-ray image classification with wavelet-based image fusion that employs deep learning algorithms and a fusion. technique to combine these

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various images into one single image of high resolution and better quality.In contrast with the methods such as weighted averaging or

maximum intensity projection this new approach is aimed at finding the features of interest in the image and packing as much information as possible in the final image. The proposed approach also minimizes on noises and artifacts which are commonly observed in the resultant image thus creating the image more precise in diagnosis as well as treatment. Moreover, the deep learning algorithms can distinguish between the tissue type thus can be of tremendous help while identifying early diseases as well as identifying abnormalities. The deep learning-based multi-spectral X-ray image fusion method has potential for numerous medical imaging tasks, including cancer diagnosis and treatment, cardiovascular disease detection and treatment, and others. By allowing the delivery of more accurate and detailed images, this technology can make medical diagnoses and treatments much more effective and accurate.

2. Related work

Different techniques have been developed for multi-spectral X-ray image acquisition and processing, including spectral imaging, dual-energy imaging, and photon-counting imaging. These techniques rely on the use of dedicated software and hardware for acquisition and processing of the multi-spectral X-ray images.Examples of the research done on multi-spectral X-ray imaging include that by [1], who employed spectral imaging in order to increase the accuracy of lung nodule detection. Another and an example being the work of [2], in which they developed a multi-spectral X-ray imaging system for the study of cultural heritage artifacts.X-ray imaging in veterinary practice involves the diagnosis of animal diseases such as fractures, arthritis, and respiratory diseases. X-ray imaging is also employed in animal observation and wildlife conservation to study animal anatomy and physiology [3].

Image fusion techniques are used to merge several images of the same scene acquired by different sensors or imaging modalities into a single image that improves information content and overall image quality. Remote sensing, medical imaging, surveillance, and robotics are just some of the uses of these techniques. However, image fusion techniques have constraints that should be grasped in order for them to be used successfully and effectively [4].

Image fusion methods, on the contrary, have generic applications and are beneficial to enhance image quality and information content. Constraints like loss of information, artifacts and noise, computational complexity, and absence of standardization must be considered, however. Future research will entail the development of new algorithms that break through these constraints, and standardization efforts will ensure interoperability and consistency across different systems and applications [5].

The computational cost necessary for image fusion can also be a limitation since it can be computationally expensive and require huge amounts of processing power and time. This is particularly undesirable when dealing with big data or real-time applications where efficiency and speed are essential [6].

Deep learning-based image fusion techniques are emerging methods utilizing artificial neural networks for the task of combining numerous photographs of a single and identical picture into an image with greater details and higher quality than one of the provided input images alone. These kind of input photos may come from various sources of various sizes and resolutions [7].

Other deep learning-image fusion methods, such as generative adversarial networks (GANs), employ more sophisticated architecture. They train two neural networks: the first to generate the fused image and the second to estimate whether the image is real or generated. The two networks are both trained in an environment that resembles a game in which the generator attempts to generate images that will deceive the discriminator and the discriminator attempts to become capable of distinguishing real from generated images [8].

The work in [9] introduces VGG-FusionNet, a new deep learning algorithm for COVID-19 diagnosis using both chest computed tomography (CT) scan and chest X-ray (CXR) images. The approach seeks to correct the shortcomings of existing work by combining CT scan features and CXR image features, eliminating bias caused by unavailability of demographic in-formation for the dataset, and testing for generalizability on more than one data source. To obtain features from CT scan and CXR images, the following system employs convolutional layers of the three pre-trained models, i.e., GoogLeNet, ResNet, and VGG. The features that are extracted are merged and employed for training fully connected layers.As is reported by the authors, using the convolutional layers of VGG resulted in the overall best performance and an accuracy of 0.93. Overall, the proposed VGG-FusionNet model outperforms most other deep learning models that take only features of CT scans or CXR images for COVID-19 detection on both CT scan and CXR images.

Detection of COVID-19 is crucial in limiting the propagation of the virus and preventing harm to the body's organs, particularly the lungs. One viable approach explored in [10] involves the use of CoviNet, a deep learning network that can detect the existence of COVID-19 in X-ray images of the chest. The architecture of CoviNet encompasses an adaptive histogram, equalization, median filter and an end-to-end trained CNN on publicly available datasets. The model achieved high performance for both binary classification (98.62%) and multi-class classification (95.77%) and can therefore be utilized as an effective tool to assist radiologists in COVID-19 diagnosis.

The researchers also discussed the application of deep learning models for the detection of COVID-19 from chest X-rays in [11]. As the virus attacks respiratory epithelial cells, X-rays can be utilized to ascertain the patient's lung condition. Deep learning-based recommender systems can prove to be beneficial in cases where there are a high number of patients and a shortage of radiological experts. The researchers used pre-trained models to create an image classification model in which COVID-19 can be predicted by using images of chest X-ray. Compared to other models, they determined that the most accurate model was DenseNet201 (96.54%). This model is downloadable by any medical professional on any device and can be used to detect COVID-19 positive cases with ease through the use of chest X- ray scans

Covid-19 virus first broke out in China and quickly spread around the world, as observed in a recent study by [12]. It is crucial to detect positive patients at an early stage so that the outbreak won't get any further spread. RT-PCR test and radiographic chest imaging are critically used during the diagnosis phase. ResNet50 model, which belongs to a convolutional neural network architecture, was utilized to detect Covid-19 from chest x-ray images. Images from chest x-rays can be examined using artificial intelligence to quickly detect infected patients. The experimental results of the study are promising, indicating that computer-aided diagnosis can work in pathology. It can also be useful when RT-PCR is not available or when doctors or radiologists are not present.

The researchers utilized the transfer model ResNet-50 to label chest x-ray images of both Covid-19 and non-Covid-19 patients. It was found that the accuracy in classification was 99.5 percent, demonstrating that such an application would be beneficial in the actual clinical environment. Despite the limited dataset, this work has potential for the use of computer-aided analysis in pathology.

The goal in [13] was to construct deep convolutional networks for classifying X-ray images as normal, viral pneumonia, or COVID-19. Different data sources were utilized to improve the generalization power of the networks. However, the small quantity of COVID-19 data available was a major problem in creating automatic classification algorithms. Despite this difficulty, the researchers were able to obtain over 500 X-ray images of COVID-19 positive patients, a significant jump from earlier research. The objective of the study was to compare the performance of various net- works on the COVID-19 classification task. The addition of the viral pneumonia class enhanced the model's sensitivity. The Xception model gave better results compared to the other eight models under consideration on all the performance measures. The research contributes to recent attempts at detecting COVID-19 cases early, which would help clinicians make a diagnosis. The researchers intend to use labeled tagging in future work to attract radiologists' attention to the region of interest. The researchers also intend to explore cross-validation methods, which would be helpful in solving medical problems. Overall, the study shows the potential of deep convolutional networks for assisting medical professionals in detecting and diagnosing COVID-19.

The paper in [9] proposes a new deep model called VGG- FusionNet. The architecture combines CT scan and CXR image features and addresses some of the shortcomings in earlier research. They are susceptible to bias due to limited demographic data available in the database, non-reproducibility, and a lack of consideration for generalizability across many sources of data. ResNet, GoogLeNet, and VGG convolutional layers were used and concatenated with fully connected layers during training to learn features from CT scan and CXR images.. Our results showed that the VGG convolutional layers worked best overall with a classification accuracy of 0.93. Deep learning methods that only use CT scans or CXR image features are better than our approach. VGG outranked the other two feature extraction algorithms (GoogleNet and ResNet) using accuracy and AUC. Thus, they utilized the VGG convolutional layer for feature merging and extraction and the VGG full connected layers for training in order to create our baseline model. With an in- ternal testing the accuracy is 0.9 and an AUC is 0.93, the baseline model was better than other deep learning models.

The AUC and accuracy of the other two models were much lower than the baseline model. Thus, external reviews were not performed on them. The baseline model was externally tested instead, with an accuracy of 0.79 and an AUC of 0.84. The baseline model performed well in accuracy and AUC in both internal and external testing and can be utilized to serve as a benchmark for future experiments. The results demonstrate the effectiveness of applying VGG's convolutional layers for fusion and feature extraction followed by full connected layers to be an effective way for fusing CT scan and CXR images. High accuracy and AUC of the baseline model demonstrate that the model has the ability to improve diagnosis and treatment of medical diseases that require the interpretation of CT scan and CXR images.

3. The proposed Method

3.1. Dataset selection

In this paper, a dataset of chest x-ray images was gathered by the National Institutes of Health (NIH), as described in the paper [15]. The first dataset had 112,120 images of which all images were in the images-224 folder. A total of 15,403 patients were represented in the dataset with one or more chest x-ray images per patient. In addition to the images-224 folder, a Data_Entry_2017 Excel file was provided. The Excel file contained relevant information connected to each image, such as the identifiable disease in the chest x-ray, patient ID connected to the image, patient age, gender, and image view positionThree diseases were selected, and a subset of images was generated using the information in the corresponding dataset. The diseases chosen were pneumonia (Figure 1), pneumothorax (Figure 2), and cardiomegaly (Figure 3). Subsequently, to prepare the data for analysis, the images were sorted into categories based on the visible disease. All the images connected to one patient were also grouped for use in a fusion algorithm. The dataset was then split into the training set and the testing set.

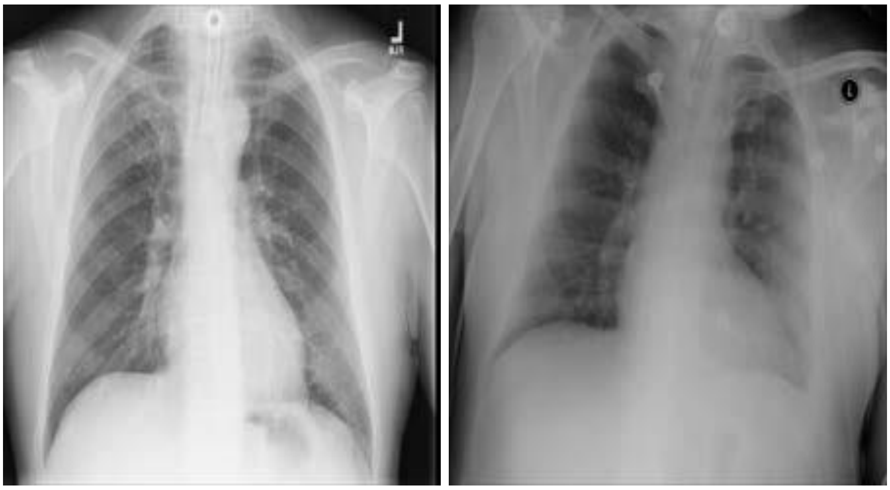


Fig.1. pneumonia images

Fig.2. pneumothorax images

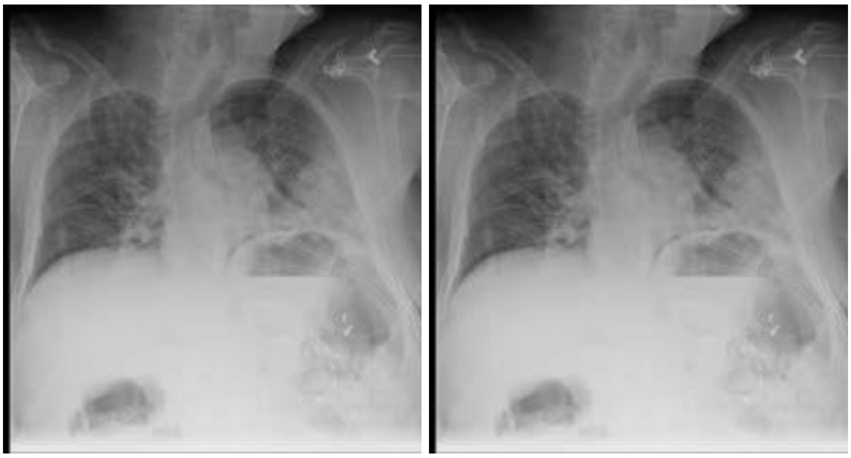


Fig.3.cardiomegaly images

1.1. Pre-processing

To summarize the process, the following steps were taken:

- The data set will be divided into training and testing sets, with around 80% of the data used for training and 20% for testing. The data will be divided based on the patient ID, so that images from the same patient are either in the training or testing folder.
- For every patient, folders were created that fell under the train and test folders, with the images for that patient put into their respective folders according to their patient ID. For each patient, the wavelet transform image fusion algorithm could then be run on the specific patient's images. The final data set was organized with train and test folders, with subfolders for healthy, cardiomegaly, and pneumothorax, and subfolders inside each disease folder that contained each unique patient's x-ray images. The data cleaning script only describes step three in the pipeline.
- After the dataset was organized, the image fusion algorithm was applied to each unique patient's x-ray images using the wavelet transform. This algorithm combined multiple images of the same patient to produce a single fused image with richer information. The resulting fused images were then used for training and testing machine learning models to classify the x-ray images into their corresponding disease categories.

1.2. Fusion method

Image fusion, as shown in Figure 4, is done by combining information from several images of the same scene, especially x-ray images and multispectral images, into one single image to obtain better image resolution. This, in turn, helps reduce diagnosis errors in chest x-ray images. Once different images for the same patient are available, they can be fused together to produce a better image with richer information. Different approaches are used for image fusion, including high-pass filtering technique, IHS transform-based image fusion, PCA-based image fusion, and wavelet transform image fusion. In this approach, the wavelet transform was used.

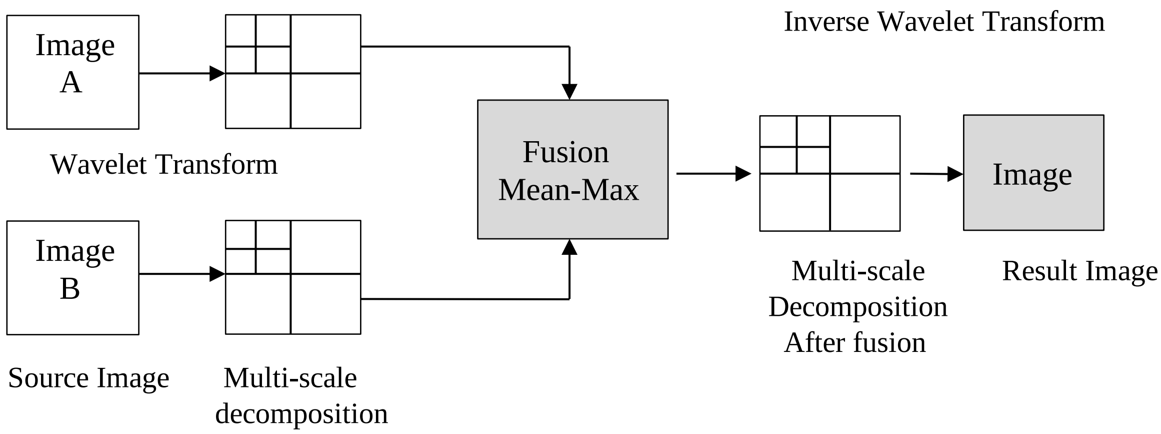


Fig.4. fusion process using wavelet

(A) Patient Image 1 (Before) (B) Patient Image 2 (Before) (C) Patient Image (After)

Fig.5. illustrates a comparison of patient images before and after fusion.

Wavelet transformations are high pass filtering extensions. The application of DWT (Discrete Wavelet Transform) can be visualized as a bank of filters. The signal is separated into high frequency and low frequency components at each level of decomposition; the low frequency components can be further decom- posed until the desired resolution is obtained. The Discrete Wavelet Transform (DWT) is a versatile mathematical tool used in signal processing and analysis. It can divide a signal into several sub- bands that record different scales of change in the signal. This change can be described as a range of filters, each of which captures a particular band of frequencies. The DWT works by recursively separating the signal into two parts: In other words, it is a structure that features low-frequency and high-frequency details. The first part gets the overall variation of the signal, the second part gets the detailed variation of the signal. When DWT is applied to the signal low frequency component, it forms multi resolution representation of signal which can be used for the various signal processing applications such as image compression, denoising, feature extraction and time series analysis. The number of decomposition levels can therefore vary due to the length of the signal and the wavelet used in the transform. The filters that have been used in the DWT are orthogonal or biorthogonal so as not to have their supports overlap in the frequency space. In conclusion, the DWT turns out to be very convenient in the field of signal processing and gives researchers as well as engineers an efficient way to analyse signals and process them.

Implementation of Wavelet transform:

Two directories called train_f_used and test_fused were created to contain the fused images, with each directory having sub-folders for each class: pneumonia, pneumothorax, and cardiomegaly.To apply the fusion algorithm using the wavelet transform the following steps were applied for each folder containing the patient's chest images:

1. The images were changed from RGB to grayscale to enable the application of the algorithm**.**
2. The wavelet transform is applied to each set of input images using the Py-Wavelet library in Python, allowing the extraction of coefficients from each image**.**
3. The fusion is applied to the coefficients for each level in the images using the mean method, where the mean of the coefficients extracted from each level of the input images is calculated.
4. The fused coefficients are transformed back to obtain the image by applying the inverse wavelet transform.
5. The image is saved in its corresponding folder, either train_fused or test_fused, and in its appropriate sub-folder: pneumonia, pneumothorax, or cardiomegaly, according to the diagnosed disease. As a result, two new datasets (train_fused and test_fused) are created, containing the fused images for each class, enabling the application of the classification algorithm on this new dataset

4. Network Architecture

The model described appears to be a convolutional neural network (CNN) for image classification with three classes: pneumonia, pneumothorax, and cardiomegaly. CNNs are particularly effective at learning features from images by using convolutional layers to extract low-level features, such as edges and shapes, and high-level features, such as textures and patterns.
The model structure involves four convolution layers where filters are applied on the input image to obtain feature map. The ReLU activation function is often used in the convolutional layers as they introduce the non-linearity to the model enhancing the learning process,The size of the filters used in the convolutional layers is 3x3, which is a common size used in CNNs.

1. The four max-pooling layers in the model serve to reduce the dimensionality of the feature map generated from the convolutional layers through the pooling operation, which computes the maximum value within each pooling window. The objective of the max-pooling layers is to reduce the size of the feature maps and thus the computational complexity of the model.
2. Batch normalization is employed in order to provide more stability during a model's training process, help the model converge faster, and also reduce the risk of overfitting. In other words, when a neural network uses Batch Normalization, it normalizes the layer activation for every batch, which can improve stability and learning time during the training process.
3. a dropout layer is introduced after batch normalization to randomly nullify some activations. This strategy is employed to reduce overfitting by decreasing the correlations between neurons in the model.
4. To flatten the 2D feature map into a 1D feature vector that can be used by a fully connected dense layer, add a flatten layer. Additionally, the input layer should include a fully connected dense layer for learning intricate non-linearities between characteristics and categories. The ReLU activation function is also widely applied in this layer to enable non-linearity of the model. For multi-class classification, the final output layer is a dense layer with a soft- max activation function. The softmax function returns a probability distribution over the three classes, with the highest probability class chosen as the predicted class.

Overall, the model architecture is well-designed, with a decent mix of convolutional and fully connected layers. By minimizing the risk of overfitting, the employment of batch normalization and dropout layers improves model performance. The model's performance, on the other hand, will be decided by the quality and quantity of training data, as well as the hyperparameters used throughout the training process.The model diagram is presented in Figure 7.

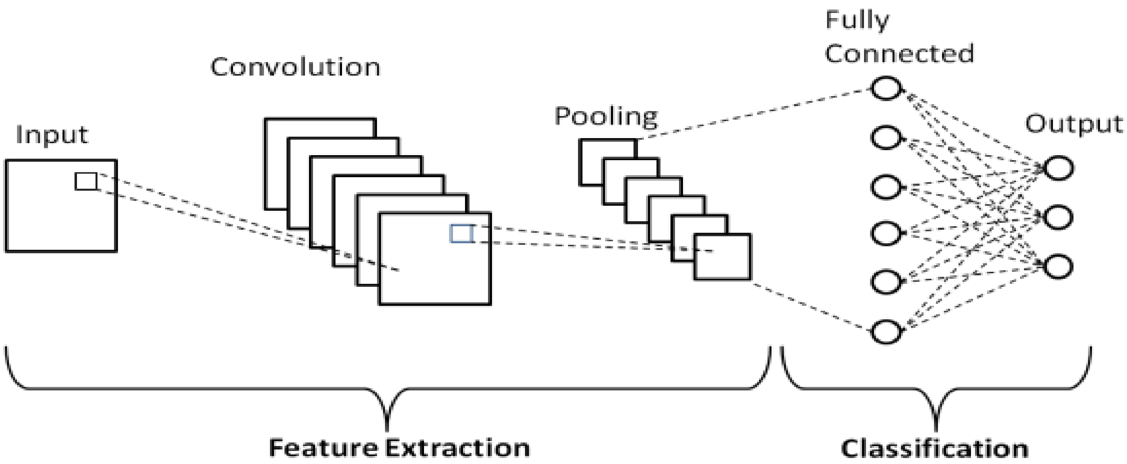
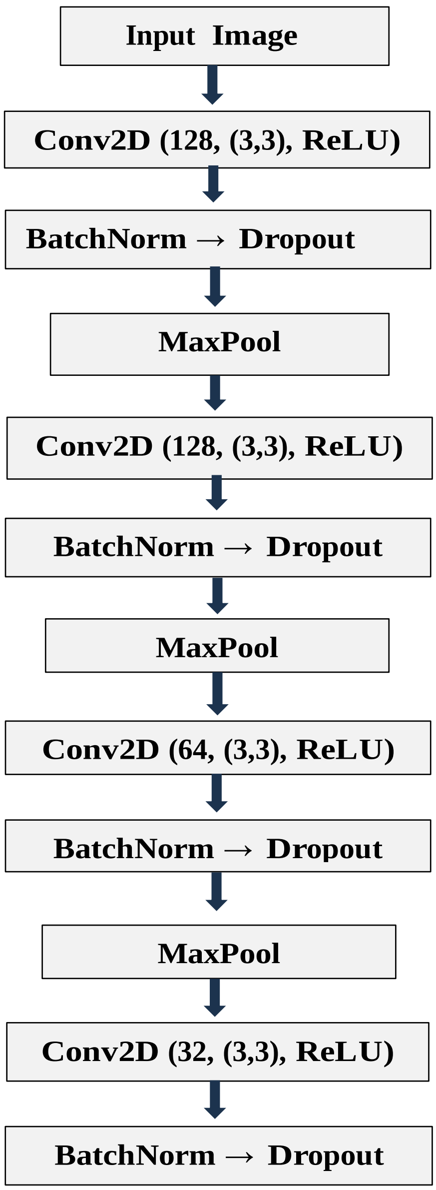


Fig.6. Schematic diagram of a basic convolutional neural network (CNN) architecture [8]



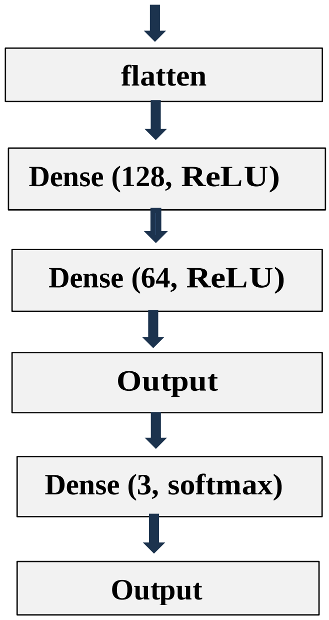


Fig.7. architecture diagram of the CNN model

5. Experimental Results

5.1. Simulation result for testing

The given result, in Figure 8, indicates that the model has been trained for 100 epochs on the dataset using Google Colab and has achieved an accuracy of 95% on the training data and 90% (above 90% for certain epochs).

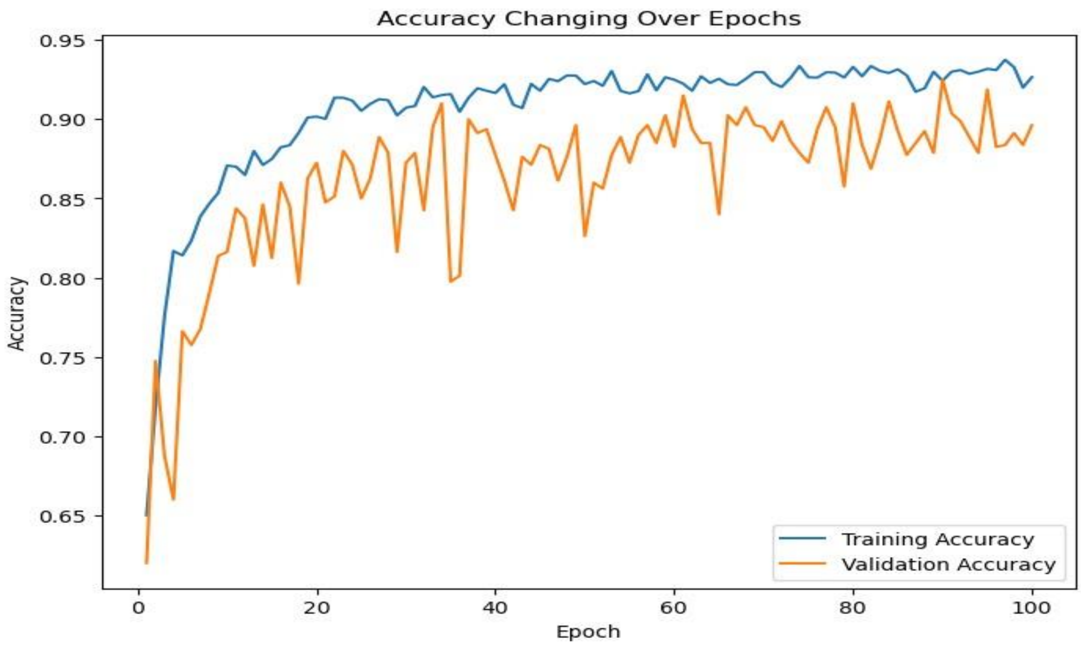


Fig.8. system accuracy for train and test

The first reason is related to the dataset used for training the model. The statement suggests that the x-ray images may not be very clear, which could be a challenge for classification. Additionally, the size of the training dataset is small, which may lead to overfitting of the model on the training data. There- fore, more data may be required to train the model to generalize better and achieve higher accuracy.

The second reason that can be mentioned is related to the fusion algorithm used for the classification. It may not be suitable for the given dataset, and as a result, it may not have given the desired result. Therefore, exploring other algorithms and techniques for fusion may be necessary to improve the accuracy of the model.

In summary, the given result offers insights into the performance of a model on a certain dataset, while also emphasizing the need to address challenges related to both the dataset and the algorithm used for classification in order to achieve higher accuracy. On the other hand, the achieved accuracy is considered very good despite these challenges.

5.2. Simulation result for validation

The Table 1.shows the precision, recall, and F1-score for each of the three classes in a classification task, where the classes are cardiomegaly (0), pneumonia (1), and pneumothorax (2).

Table 1. Classification Report

Class	Precision	Recall	F1-score
Cardiomegaly (0)	0.88	0.90	0.89
Pneumonia (1)	0.84	0.80	0.82
Pneumothorax (2)	0.85	0.86	0.85

- For the class "Cardiomegaly," the precision is 0.88, which indicates that when the model predicts Cardiomegaly, it is correct around 88% of the time. The recall is 0.90, suggesting that the model can correctly identify around 90% of the actual Cardiomegaly cases. The F1-Score, which balances precision and recall, is 0.89.
- Fortheclass"Pneumonia,"theprecisionis0.84, indicating that the model’s predictions for Pneumonia are accurate approximately 84% of the time. The recall is 0.80, implying that the model can identify around 80% of the actual Pneumonia cases. The F1-Score for this class is 0.82.
- For the class "Pneumothorax," the precision is 0.85, indicating that the model’s predictions for Pneumothorax are accurate approximately 85% of the time. The recall is 0.86, suggesting that the model can identify around 86% of the actual Pneumothorax cases. The F1-Score for this class is 0.85.

These metrics provide insights into the performance of a classification model, assessing both its ability to make correct predictions (precision) and its ability to capture the relevant instances (recall). The F1-Score combines these metrics into a single value that represents the overall effectiveness of the model in terms of precision and recall.

The confusion matrix for the test is shown in Figure 9

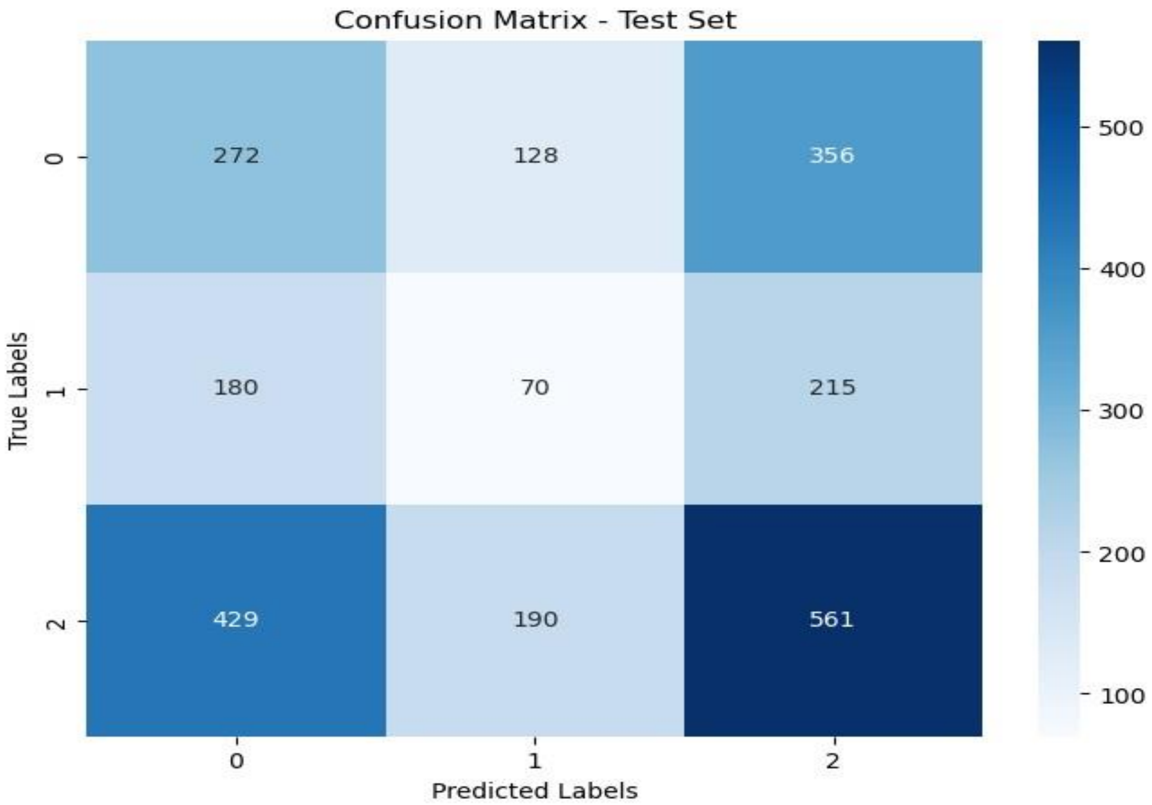


Fig.9. Confusion matrix of test

6. Comparative analysis

The Table 2. provides a comparative analysis of the accuracy and usage of image fusion in various studies that have utilized CNN algorithms for classification tasks.

Table 2. Comparative analysis with existing work

Reference	Used algorithm	Application	Accuracy	Does Image Fusion used?
[9]	CNN	CT scan and Chest X-ray	0.93	No
[11]	CNN	Detecting covid-19 from Chest X-Ray	0.96	No
[14]	CNN	Ship Classification	0.9	Yes (High resolution images)
proposed Algorithm	CNN	Multi spectral X-Ray images	0.9 (0.95 for some	Yes (Low quality Images)

The first three references have used CNN algorithms to classify chest X-rays or CT scans for different purposes such as detecting COVID-19 or identifying various chest abnormalities. These studies have reported high accuracy rates ranging from 0.93 to 0.96 without using image fusion.

The third reference has used CNN to classify ship images with a slightly lower accuracy of 0.9. However, this study used high-resolution images and applied image fusion.
Finally, the proposed algorithm in this study has used CNN to classify multi- spectral X-ray images and has achieved an accuracy of 0.9 and above (in some epochs gives an accuracy 0.95) with the usage of image fusion. The interesting aspect of this study is the usage of low-quality images and still achieving a high accuracy rate with image fusion.

7. Conclusion

Image fusion is an essential technique used in various image processing ap- plications, such as medical diagnosis, remote sensing, and surveillance. The primary objective of image fusion is to combine two or more images to create a more informative and visually appealing image. Deep learning techniques such as convolutional neural networks (CNN) have recently shown significant promise in image fusion applications. The present master thesis proposes a new deep learning-based multi-spectral X-ray image fusion method that utilizes CNN and wavelet transform to enhance the quality of multi-spectral X-ray images. The proposed method de- composes the image using wavelet transform and then employs a CNN to fuse the multi-spectral X-ray images. The accuracy of the proposed model was evaluated using both the training and test data. The results demonstrated that the model achieved an accuracy of approximately 95% on the training data and 90% on the validation data. In some epochs, the accuracy reached 0.95. Our proposed algorithm exhibits a high level of accuracy when compared to other algorithms reported in the literature. It is important to note that the quality of the input images is not particularly high, and a fusion method is utilized to combine information from multiple images.. These factors could potentially impact the accuracy of our algorithm. However, despite these challenges, our algorithm still achieves an impressive level of accuracy.

Finally, the primary advantages of the proposed algorithm are twofold. Firstly, it achieves a high level of accuracy when using fused images. Secondly, the algorithm is able to achieve this high level of accuracy while using low-resolution fused images.

The proposed method has several potential applications in medical diagnosis and treatment planning. The accurate fusion of multi-spectral X-ray images can provide better insights into the tumor's shape, size, and location, which can help clinicians to plan the treatment effectively. Additionally, the proposed method can also be used for image registration, where multiple images need to be aligned to create a single image with improved quality and accuracy. However, the proposed method has certain limitations that require further research. For example, the method was evaluated on a limited dataset, and the performance may differ on other datasets. Furthermore, the proposed method was evaluated on multi-spectral X-ray images, and the generalization to other types of images may need more investigation.

Future research can explore the effectiveness of various deep learning architectures for image fusion, such as recurrent neural networks (RNN) and transformer- based models. Additionally, incorporating attention mechanisms in the fusion process may further improve the accuracy and quality of the fused images. Moreover, the proposed method can be used in other fields such as remote sensing and surveillance. The fusion of multiple satellite images can provide better insights into the earth's surface, which can help in various applications such as agriculture, urban planning, and disaster management. Similarly, in surveillance, the fusion of multiple cameras can help in tracking objects and identifying potential threats.

In conclusion, this paper proposes a new deep learning-based multi- spectral X-ray image fusion method that utilizes CNN and wavelet transform. The experimental results demonstrate that the proposed method achieves high accuracy and quality compared to several state-of-the-art methods. The pro- posed method has several potential applications in medical diagnosis and treatment planning, and future research can explore its effectiveness in other fields such as remote sensing and surveillance.

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رفع أداء تصنيف صور الأشعة السينية باستخدام دمج المويجات والتعلم العميق

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القبول	4 أيار 2025
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الكلمات المفتاحية

تصنيف صور الاشعة السينية, الشبكة العصبية التلافيفية, تحويل الموجة, دمج الصور,التعلم العميق.

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الملخص

شهد التصوير الطبي تقدمًا كبيرًا في السنوات الأخيرة، حيث كان إدخال التصوير بالأشعة السينية متعدد الأطياف أحد التطورات البارزة. ومع ذلك، فإن طرق دمج الصور التقليدية مثل المتوسط المرجح أو الإسقاط الأقصى للشدة قد لا تكون كافية لمعالجة تعقيدات صور الأشعة السينية. استجابة لذلك، تم تطوير طريقة جديدة لدمج صور الأشعة السينية متعددة الأطياف قائمة على التعلم العميق. تستخدم هذه الطريقة خوارزميات التعلم العميق لدمج الصور المتعددة التي تم الحصول عليها من مستويات طاقة الأشعة السينية المختلفة في صورة واحدة بدقة أعلى وتحسين الجودة. يسلط بيان المشكلة الضوء على قيود طرق التصوير بالأشعة السينية التقليدية والتحديات في تطوير طريقة فعالة لدمج الصورة. تعد مساهمة النهج المقترح خطوة نحو تحسين جودة ودقة التصوير الطبي، مما يؤدي إلى نتائج أفضل للمرضى وممارسات رعاية صحية أكثر كفاءة. تشير النتائج المقدمة إلى أن النموذج المقترح حقق دقة بنسبة ٩٥٪ على بيانات التدريب و ٩٠٪ على بيانات الاختبار، مع مجال للتحسين. تتم مناقشة الحد من مجموعة البيانات والخوارزمية المستخدمة للتصنيف كأسباب محتملة لعدم تحقيق دقة أعلى. هناك حاجة إلى مزيد من البحث لتطوير نماذج التعلم العميق المتخصصة لدمج صور الأشعة السينية واستكشاف الخوارزميات والتقنيات الأخرى لمواجهة التحديات المتعلقة بمجموعة البيانات والخوارزمية المستخدمة للتصنيف.

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