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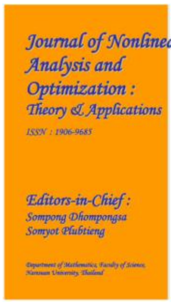

ASSESSING QUALITY OF MRI IMAGE USING CNN-BASED IMAGE QUALITY APPROACH

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ABSTRACT: MRI is indispensable in modern medicine diagnoses, but image quality evaluation is especially important in this context because it is directly related to how patients are cared for. The study looks at the use of CNNs for objective MRI image quality screening, which has the significant advantage of being objective rather than subjective. We describe a CNN model with convolutional and pooling layers that is proficient at extracting features from extremely complex patterns for image processing. The CNN model is educated by feeding it with a graphic dataset that is particularly epic in distinguishing between blurry and clear images. As a result, the outcome was accepted as being more accurate than the previous method. We created a model that can learn from photos using inter relational mathematics, such as converting images to quality ratings using end-to-end coordinates, thereby analytically eliminating a manual inspection step. The results show that deep learning approaches play an important role in a deep learning process of quality control in medical imaging, providing clinicians with more accurate information for diagnosis and more successful treatment outcomes.

Keywords: MRI, Image Quality Assessment, Convolutional Neural Networks, Deep Learning, Medical Imaging.

1. INTRODUCTION

An essential diagnostic method in today's medical world derives from magnetic resonance imaging technology (MRI), which allows medical practitioners to explore the human interior systems at depth. MRI's key strengths include its ability to display images without direct invasion and its excellent precision. Such qualities have significantly revolutionized medical imaging in the MRI technology, allowing physicians to observe inside structures and disorders in greater detail than was previously allowed. One of the most important aspects of MRI analyst work is the science of extracting valuable information from raw data. Aside from sophisticated imaging techniques, MRI scan systems are known as "perfect" because of their capacity to suppress artifacts and adjust image accuracy, bringing illness diagnostics to the highest degree. Image processing algorithms can be performed using powerful algorithms and computational techniques, resulting in the generation of clear images, noise removal, and contrast enhancement; radiologists and physicians will then have an easier time arriving at an accurate and precise diagnosis.

The primary purpose of image processing in the context of MRI is twofold: that is able to not only identify specific disorders and their severity but also allows particularly accurate formulation of management plan. Imaging technologies are designed to boost image quality and show details that may fail to be visible. Also, it assists the physicians with the accurate diagnosis of diseases via the identification of even the tiniest abnormalities and the best way of treatment. The fact that the lowering of the number of artifacts and the enhancement of image quality results in the patients needing fewer repeat scans should be liked by all patients. It also is relieving stress for many of the patients that have to endure these scary tests, as well as this shortens the whole diagnostic process. This paper is about the quality of images in MRI and using the Deep Learning approach and CNNs to assess the image. Ending up with reliable and objective scales for measuring and validation of MRI images.

2. REVIEW OF LITERATURE

In one aspect of the field of medical imaging involving Magnetic Resonance Imaging (MRI), fast and robust image quality assessment (IQA) methods can be of great interest and this is an aspect that has been the subject of current investigation [1]. IQA is indispensable in radiologist's as well as clinician's diagnostic process and, therefore, they should be made available and utilized to the extent they are instrumental to the interpretations. Along the way, researchers have been comparing the tools and approaches in the hope of finding a reliable and repeatable procedure of quantitatively assessing image quality for MRI [2]. A key research domain in the field of MRI IQA is development of objective methods and algorithms, which would be a functional tool for Perfection of image parameters; such as sharpness, noise, contrast, and artifacts content [4].

These metrics act as quantitative measurement of image quality and allow clinical niche professionals to assess the diagnostic value of the MRIs precisely [3]. The continuous examinations of Magnetic Resonance Imaging (MRI) for Instant Quality Assessment (IQA) traditionally were performed largely in the subjective manner by expert radiologists whose assessments were prone to referring variability and subjectivity [5]. Yet a lot with the appearance of machine learning and deep learning machinery, mainly Convolutional Neural Network (CNN), IQA methods have changed the curve towards objective, automated methods [7]. Convolutional-Neural-Network IQA methods take advantages of state-of-the-art deep learning technology, teaching machines to learn more complex patterns and features directly from comprehensive image datasets [6]. Different from conventional models, CNN has the ability to learn not only over large data sets marked up by humans but also find hidden details in image similarity, which are key to higher and more unified accuracy evaluation.

Within the scope of testing executing networks as decision makers in the food production domain, the cutting-edge issues to be addressed are: novel neural networks architectures design, improvement (optimization) of trainer strategies, as well as the quality assessment of the obtained by the model outcomes in relation to the values of Image quality metrics from different Datasets and imaging protocols [8]. On the other hand, researches also targeted problems like interpretability, genericity and tolerance of the variation in acquisition settings, on which the models rely.

3. PROPOSED METHOD

Along with our scientific endeavours, we are going to propose an innovative system of evaluating MRI images' standard. We use the strengths of deep learning and image processing algorithms. We integrate CNN network with them as the main tool of ours. In order to commencing our path we prepare a mixed put of MRI image that cut across the different scanning scenario and the pathologies types. These different datasets being, still, the starting point of our convolutional neural network for the assessment of image quality. The model’s learning process makes it familiar with the features of an image quality across a vast diversity of situations.

Convolutional Neural Networks (CNN)

Our process relies on the potential of the Convolutional Neural Networks (CNNs), which represent a high-tech deep learning model ideal for image analysis. A CNN operates just like a human visual system, which is excellent at identifying complex patterns and features within visual mediums. First in CNN, several layers are assembled which have their own roles in image process steps. Convolutional layers as the best filters identify nuances like edges, textures, and shapes which were present in the input images. This series of levels successfully equips the neural network the ability of perceiving the raw pixel data as meaningful representations. The convolutional layers and the pooling layers working in tandem by shrinking the generated feature maps of the convolutional layers on one hand, but retaining the important data make the network more computationally efficient.

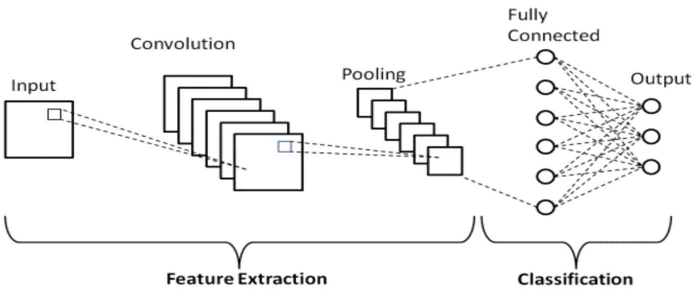


Fig 3.1 CNN ARCHITECTURE

Fully connected layers then go ahead and utilize these embedded features and use them for complex activities such as image classification and regression. In order to prevent data overfitting, a dropout layer consists of randomly deactivating certain neurons during the training process, which, in turn, enhances model generalization and reliability. ReLU or sigmoid are activation functions that bring non-linearity to the network, giving it the ability to solve the complex computational problems and learn the subtle relationships among data.

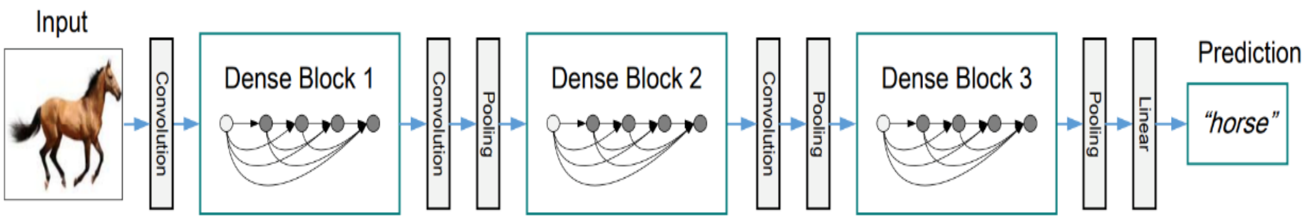


Fig 3.2 A deep DenseNet with three dense blocks.

In DenseNet architectures, linking layers is through, stronger connections are made, resulting in more effective use of features and gradient flow during training. This leads to the continuous flow of refinements that operation in different conditions, which in turns enables good quality image assessment.

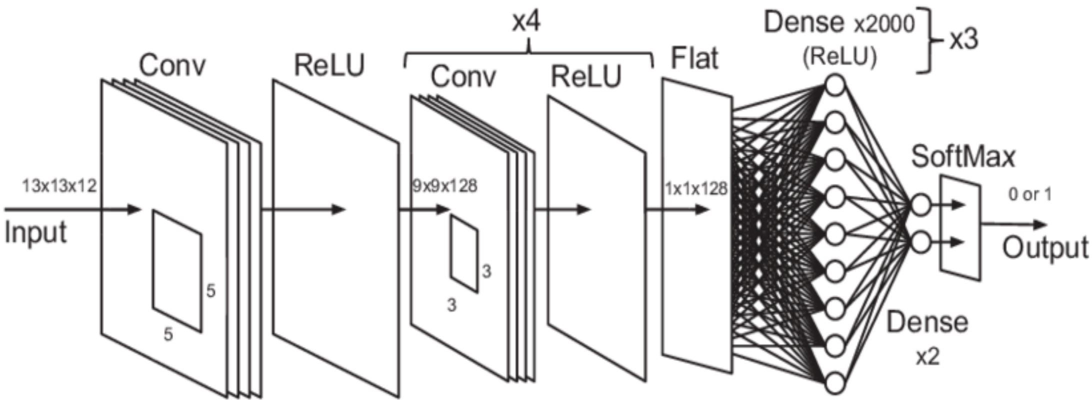


Fig 3.3 CNN architecture composed of 5 convolutional layers with 128 feature maps, 3 dense layers with 2000 neurons, and a final SoftMax dense layer with 2 neurons.

Work Flow of Our Proposed Work

Our system design provides a specialized element in the implementation of the given task (images assessments) based on practical evidence on the nature of MRI image quality. The sources or inputs of the dataset are where it all begins and thus the image processing skills such as noise detection, contrast improvements, and normalization which will be applied are our tools. Through this, we may get the pictures of the great quality and we may have an opportunity of scrutinising the material in the fine detail and performing sufficient analysis. Our setup revolves around CNN model, that is the brain of the entire system dedicated to black boxing the MRI. This model integrates a convolutive architecture with approach CNN and techniques of pooling for allowing concentration of the relevant energy of spatial resolution, noise/signal ratio (SNR) and contrast. Subsequently we execute CNN for the number of times in the learning process. In this chain the CNN learns to connect feature maps with the output quality scores via propagation backward and gradient descent. Meanwhile the evaluation metric like PSNR, MSE, and CNR are considered to promote model architecture and make sure the model work better over time. We can judge whether the algorithm is getting better or not through the evaluation metric. Making the CNN model our number one asset is what ensures that the doctors and other health professionals in the medical imaging scene use our model as the primary tool for the diagnosis and governance of their image management workflow. At that procedure, imaging modalities may be viewed as one efficiency of the comprehensive tools for early disease detection and treatment planning which in turn become more successful in organizing the quality of medical diagnosis and decrease their error rates.

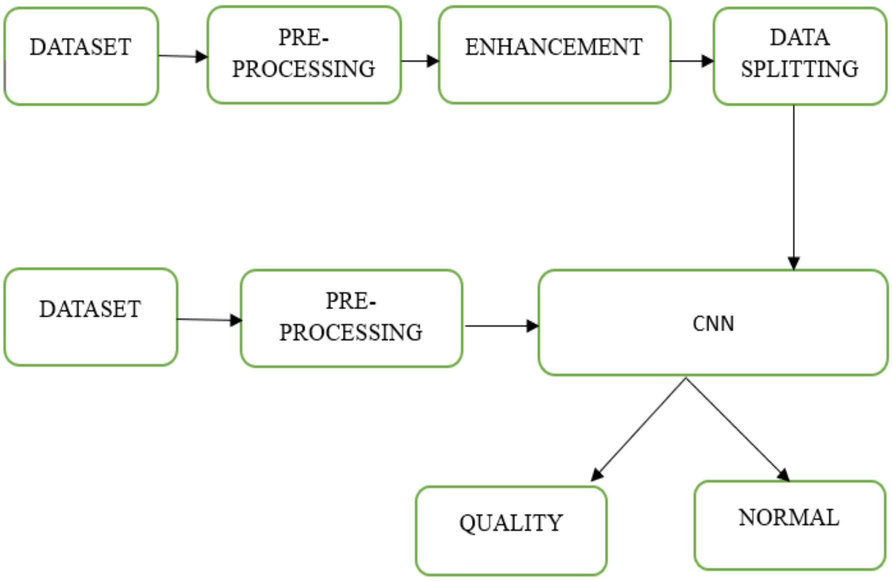


Fig 3.4 Work Flow/Block Diagram

4. RESULTS

The total dataset consists of 808 MRI images, in which the total dataset is divided into training dataset and testing dataset, which are further splits as noisy images set (233 MRI images) and sharp images set (171 MRI images). The size of the filter (kernel size) used in the convolutional layers is specified as 3x3. This is a common choice for convolutional neural networks (CNNs) and is widely used in image processing tasks. each convolutional layer is created using the Conv2D function. The kernel size parameter is set to (3, 3), indicating that a 3x3 filter is applied at each convolutional operation. This means that a 3x3 grid of pixels is used as the receptive field for each convolution operation.

Using a smaller filter size like 3x3 helps capture local patterns and features in the input images while keeping the number of parameters manageable. Larger filter sizes might capture more global patterns but can increase the computational cost and the risk of overfitting, especially in deeper networks. The padding used in the convolutional layers is specified as 'same'.

The encoder architecture comprises several layers, each with a specific configuration. These layers consist of 64, 128, and 256 filters respectively, with a kernel size of 3x3, a stride of 2, and ReLU activation function. Padding is set to 'same' to maintain the spatial dimensions of the input throughout the encoding process. The decoder, on the other hand, mirrors the encoder architecture in terms of layer configuration but in reverse order. It begins with 256 filters, followed by 128 and 64. The kernel size, stride, activation function, and padding remain consistent with the encoder. The final output consists of 3 channels for RGB images, and the activation function used here is sigmoid.

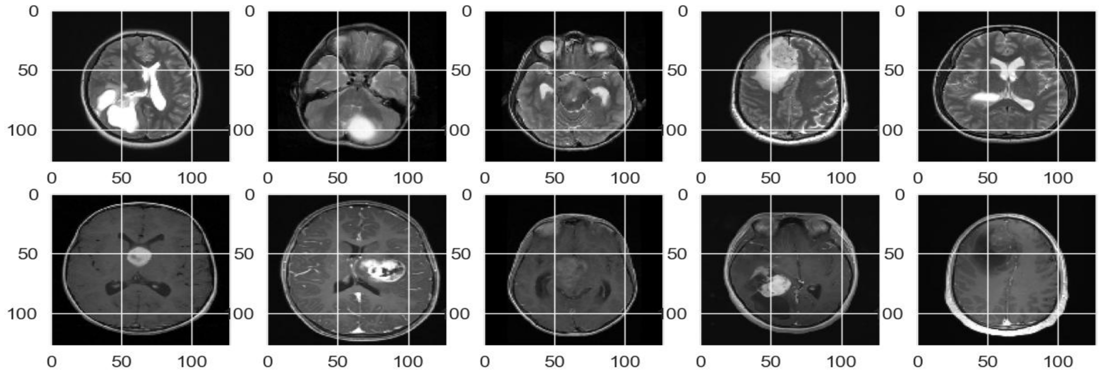


Fig 4.1 Five pairs of randomly selected clean and blurry images

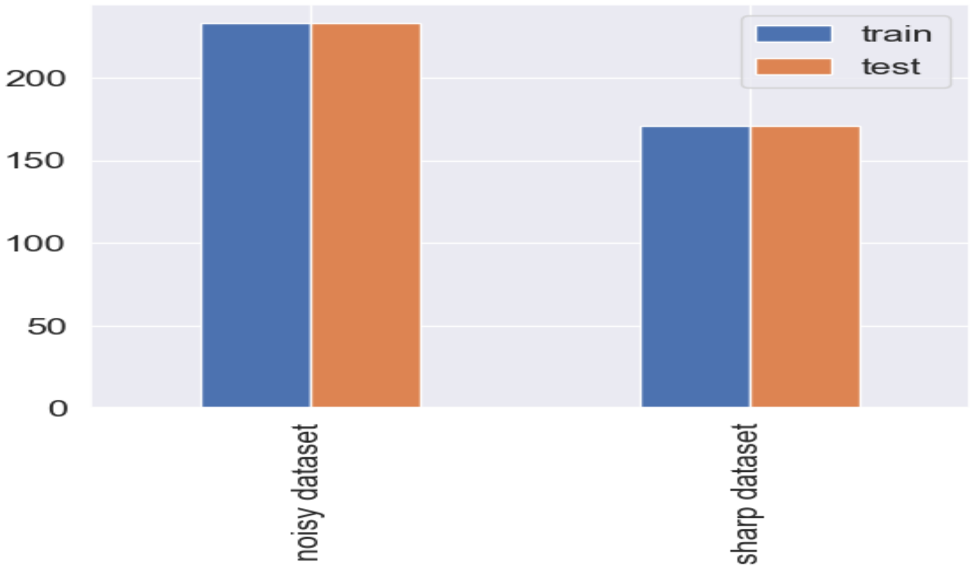


Fig 4.2 Bar plot shows the counts of each class in both the training and test datasets

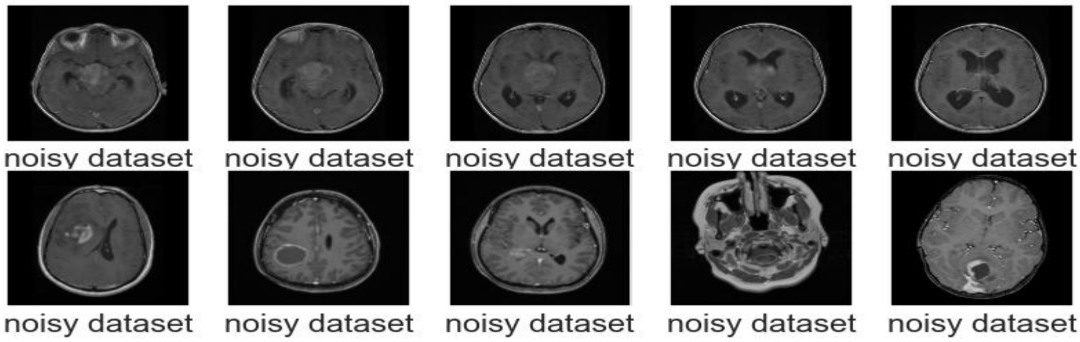
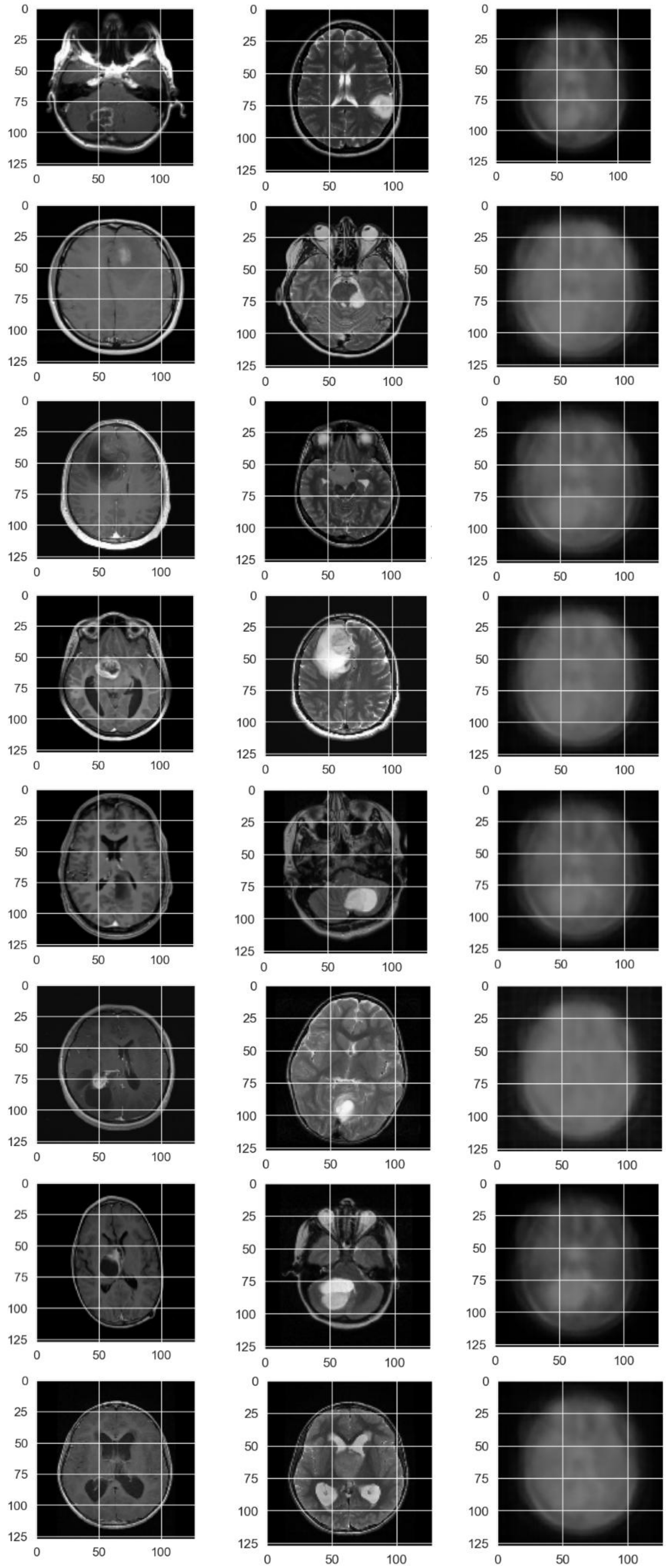


Fig 4.3 Images of the dataset

INPUT IMAGE QUALITY IMAGE NOISY IMAGE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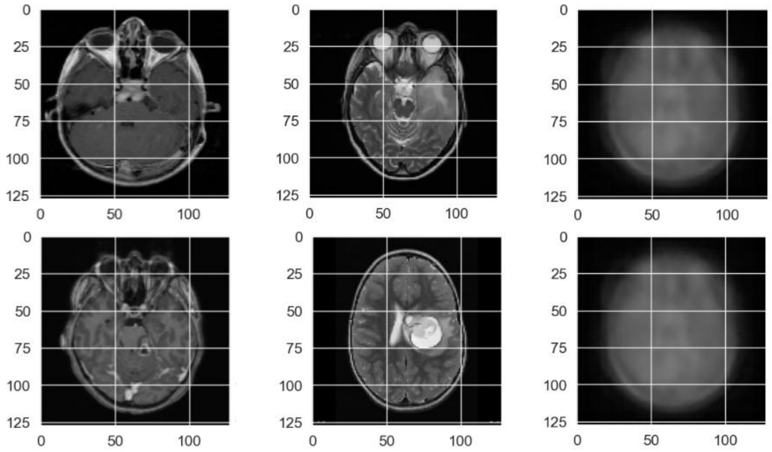

Fig 4.4 Generation of Input, Quality & Noisy Images

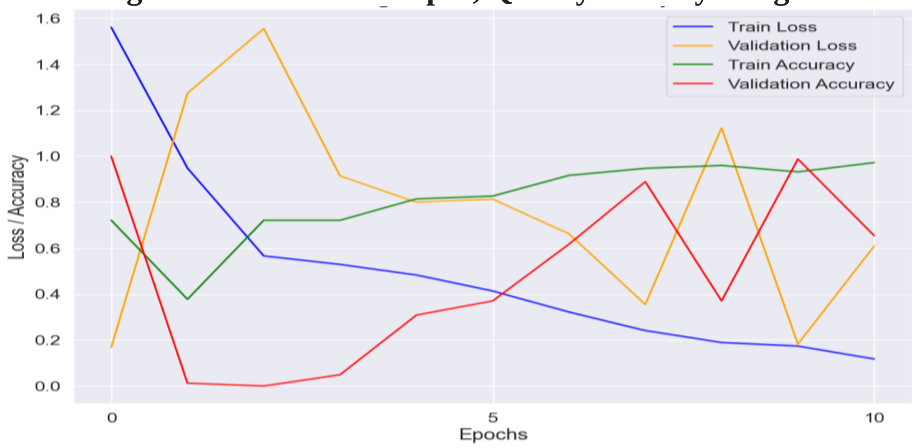

Fig 4.5 Plot for Training & Validation Loss / Accuracy

From fig 4.1 to fig 4.5 shows the results as well concludes that the Accuracy and Loss of the MRI images by a plot

METRICS CALCULATION (PSNR, MSE, CNR)

Peak Signal-to-Noise Ratio (PSNR):

PSNR is a measure of image quality, indicating how much noise is present relative to the original signal. It's calculated by comparing the maximum possible pixel value (usually 255 for 8-bit images) to the Mean Squared Error (MSE) between the clean and noisy images. The result is expressed in decibels (dB), with higher values indicating higher image quality.

- $PSNR = 10.log_{10}\left(\frac{MAX^2}{MSE}\right)$

  Where:

  - MAX is the maximum possible pixel value (typically 255 for 8-bit images).
  - MSE is the Mean Squared Error between the clean and noisy images.

Mean Squared Error (MSE):

MSE measures the average squared difference between corresponding pixel values of the clean and noisy images. It provides a quantitative assessment of the reconstruction error, where lower MSE values indicate better image fidelity. The MSE is computed by summing the squared differences over all pixels and then averaging the result.

- $MSE = \frac{1}{N}\sum_{i=1}^{N} \left(I_{clean}(i) - I_{noisy}(i)\right)^2$

  Where:

  - N is the total number of pixels in the image.
  - $I_{clean}(i)$ and $I_{noisy}(i)$ noisy are the pixel values at location i in the clean and noisy images, respectively.

Contrast-to-Noise Ratio (CNR):

CNR assesses the contrast of an image relative to the noise level present. It's calculated as the absolute difference between the mean pixel values of the clean and noisy images, divided by the square root of the average of their variances. CNR compares the signal strength (represented by the mean pixel values) to the combined noise level (estimated by the variances), with higher CNR values indicating better image contrast relative to noise.

- $CNR = \frac{|\mu_{clean} - \mu_{noisy}|}{\sqrt{\frac{\sigma_{clean}{}^2 - \sigma_{noisy}{}^2}{2}}}$

Where:

- $?_{clean}$ and $?_{noisy}$ are the mean pixel values of the clean and noisy images, respectively.
- $?_{clean}$ and $?_{noisy}$ are the standard deviations of pixel values in the clean and noisy images, respectively.

Table 4.1 Metric calculations for input ten images

METRICS	PSNR	MSE	CNR
0	15.307131	0.029464	0.153933
1	16.974710	0.020069	0.220428
2	18.056164	0.015645	0.211337
3	17.600845	0.017375	0.178192
4	17.189322	0.019102	0.085381
5	16.831254	0.020743	0.177787
6	15.418454	0.028718	0.347060
7	16.338552	0.023235	0.083741
8	16.050610	0.024828	0.280948
9	15.398601	0.028850	0.048845

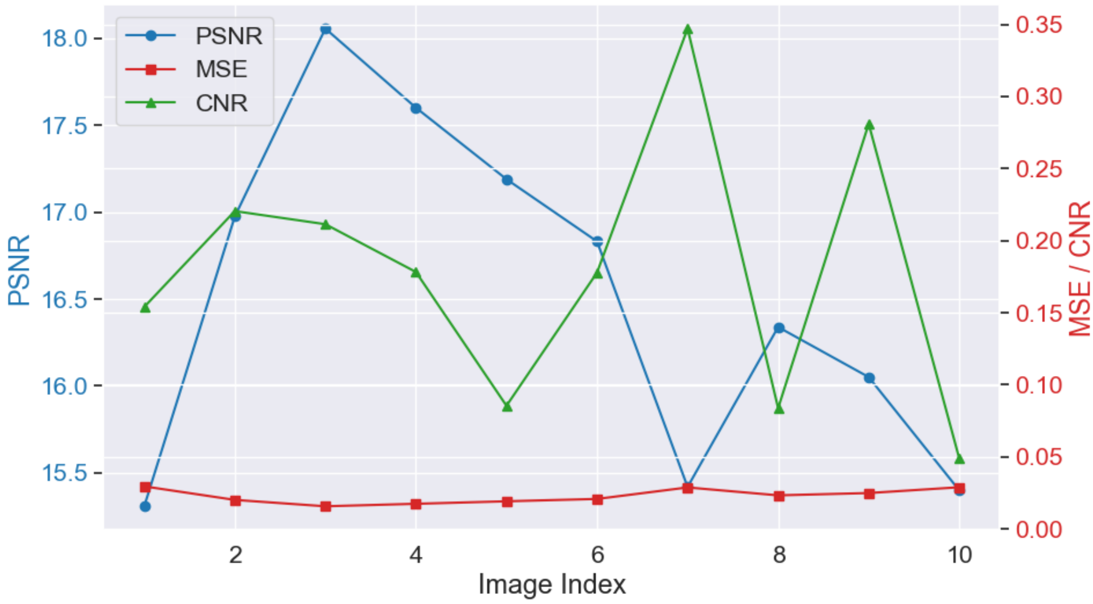

Fig 4.6 Plot for Comparison of PSNR, MSE, and CNR

5. CONCLUSION

Finally, in this piece of work, we demonstrated that utilizing Convolutional Neural Networks (CNNs) improved MR image quality assessment (IQA), increasing the accuracy and reliability of diagnostic processes. With our tried-and-true strategy of rigorous data collection, preprocessing, and model training, we have created a compelling CNN-based MRI Image Quality Assessment tool that is both accurate and effective. Adopting this paradigm has the potential to improve orderliness in medical imaging work streams, provide a convenient and precise diagnosis process, and, as a result, achieve better patient outcomes. There is no doubt that continuous enhancement of the proposed deep learning-based IQA system is required to ensure its widespread application and integration into a wide range of imaging settings and healthcare facilities. Aside from that, previous study will (also) determine the prospects for incorporating more complicated AI approaches to MRI IQA systems, as well as the collaboration with healthcare experts to improve the capabilities of such systems. The importance of this field will only expand as a result of the use of developing technology and interdisciplinary collaboration, as well as the creation of healthcare systems that are more united in their approach to the care of patients.

6. FUTURE SCOPE

The results of this work are primarily focused on developing an algorithm to monitor the objectivity of MRI scans and envisioning the necessary improvements to medical imaging technology. In terms of the future roadmap, one potential strategy for progress is to use a variety of AI techniques such as deep learning and reinforcement learning to improve the current quality assurance CNN (IQA-CNN) model. Improving MRI scan results by applying cutting-edge algorithms and models can boost the accuracy and precision of these pictures, resulting in more precise diagnoses and treatments. Furthermore, this technology could be utilized for procedures other than MRI; for example, computed tomography (CT) and ultrasounds can be widely used in a variety of healthcare settings. On the other hand, collaboration with health care experts, scientific researchers, scientists, and engineers will aid in the development of specialized machine learning models for specific diseases, healthcare environments, and imaging equipment. Through refinement in research and innovation, our organization will succeed in pushing the trend of medical imaging techniques while also making the healthcare delivery system more effective and the health outcomes healthcare process more successful. Challenges such as interpretability, ethical considerations, and validation on diverse datasets need to be addressed. However, the future holds great promise for the application of CNNs in Image Quality Assessment for Magnetic Resonance Imaging, contributing to advancements in medical imaging and patient care.

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