

IMAGE RECONSTRUCTION METHOD FOR ULTRAFAST ULTRASONIC IMAGING BASED ON CONVOLUTIONAL NEURAL NETWORK

A Project Report Phase - II

Submitted in partial fulfilment of the requirements for the award of
Bachelor of Engineering degree in Electronics and Communication Engineering

by

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
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SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

Accredited with Grade "A" by NAAC
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BONAFIDE CERTIFICATE

This is to certify that this Final Year Project Report is the bonafide work of **RAPETI CHOSHMITHA (39130369)** and **RAJANA ROSHINI (39130366)** who carried out project entitled "**IMAGE RECONSTRUCTION METHOD FOR ULTRAFAST ULTRASONIC IMAGING BASED ON CONVOLUTIONAL NEURAL NETWORK**" under my supervision from NOVEMBER 2022 to APRIL 2023.

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ABSTRACT

This project describes the Ultrafast ultrasound (US) revolutionized biomedical imaging with its capability of acquiring full-view frames at over 1 kHz, unlocking breakthrough modalities such as shear-wave elastography and functional US neuroimaging. Yet, it suffers from strong diffraction artifacts, mainly caused by grating lobes, sidelobes, or edge waves. Multiple acquisitions are typically required to obtain a sufficient image quality, at the cost of a reduced frame rate. To answer the increasing demand for high-quality imaging from single unfocused acquisitions, the proposed method consists of a two-step convolutional neural network (CNN)-based image reconstruction method, compatible with real-time imaging. A low-quality estimate is obtained by means of a back projection-based operation, akin to conventional delay and-sum beamforming, from which a high-quality image is restored using a residual CNN with multiscale and multichannel filtering properties, trained specifically to remove the diffraction artifacts inherent to ultrafast US imaging.

To account for both the high dynamic range and the oscillating properties of radio frequency US images, we introduce the mean signed logarithmic absolute error (MSLAE) as a training loss function. Experiments were conducted with a linear transducer array, in single plane-wave (PW) imaging. Extensive numerical evaluations demonstrate that the proposed approach can reconstruct images from single PWs with a quality similar to that of gold-standard synthetic aperture imaging, on a dynamic range in excess of 60dB. In vitro and in vivo experiments show that trainings carried out on simulated data perform well in experimental settings.

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CHAPTER 1

INTRODUCTION

1.1 ULTRASOUND IMAGING

Ultrasound (US) imaging is one of the most widely used medical imaging modalities, thanks to being nonionizing, and having a greater cost-effectiveness and portability compared with X-ray computed tomography (CT) or magnetic resonance imaging (MRI). Pulse-echo US imaging is typically performed by transmitting short acoustic pulses through a medium of interest using an array of transducer elements, and receiving echoes backscattered from local variations in acoustic impedance. Compared with conventional line-by line scanning, where sequential pulse-echo acquisitions are performed using focused transmit beams for each image scan line, ultrafast US imaging relies on the insonification of the entire field of view at once by transmitting a single unfocused wavefront, such as a plane wave (PW) or a diverging wave (DW).

This strategy allows for extremely high frame rates of multiple kilohertz limited only by the roundtrip time-of-flight of the transmitted wavefront. Coupled with advances in electronics and software-based delay-and-sum (DAS) beamforming, ultrafast US imaging unlocked, in the past two decades, breakthrough imaging modalities such as shear-wave elastography functional US neuroimaging ultrasensitive 2-D motion estimation and high frame-rate vector flow imaging. The main disadvantage of ultrafast US imaging using single unfocused transmit wavefronts is a decrease in image quality. Indeed, compared with a focused transmit beam which concentrates most of its energy in a limited region of interest (ROI), the energy of an unfocused wavefront is spread over the entire field of view, resulting in backscattered echoes of lower amplitude and measurements with lower signal-to-noise ratio (SNR).

The absence of transmit focusing also results in a broader main lobe of the point spread function (PSF), consequently degrading the image resolution.

Furthermore, diffraction artifacts, such as the ones caused by grating lobes (GLs), side lobes (SLs), and edge waves (EWs), are more pronounced in ultrafast US imaging. These artifacts can hamper lesion detectability and displacement estimates especially when imaging highly heterogeneous tissue. A common strategy to increase image quality in ultrafast US imaging consists of coherently compounding low-quality images obtained from multiple, differently steered, unfocused transmit wavefronts. While this method successfully improves the image quality by increasing the number of steered acquisitions, it inevitably comes at the cost of lower frame rates, larger data transfers, and increased computational requirements, as multiple transmit-receive events and image reconstruction processes are required. Synthetic aperture (SA) imaging is another acquisition strategy based on the coherent compounding of multiple low-quality images, for which each transducer element is used in sequence to transmit a wide DW. As sequential transmit-receive acquisition events are required for compounding methods, they are also subject to potential inter-acquisition tissue motion, which results in blurring artifacts. Coherent compounding techniques may not be deployable in some applications, such as those with extreme displacement estimation constraints or low-power requirements, where only a minimum number of transmit-receive events may be performed.

The main objective of this work is to provide images with a minimum amount of diffraction artifacts at the highest possible frame rate. Inspired by regularized regression methods, we propose a “two-step” image reconstruction approach, consisting of a back-projection operation to obtain a low-quality image estimate, followed by applying a CNN trained to restore a high-quality image. The back-projection operator is derived from linear acoustics and far-field assumptions, resulting in an operation similar to DAS beamforming, and is further improved with a re-weighting operation. The CNN architecture with notable improvements over our preliminary work. To account for the high dynamic range (HDR) property of US images while preserving their radio frequency (RF) nature, we introduce the mean signed logarithmic

absolute error (MSLAE) as a training loss function. Experiments were conducted on a linear transducer array using a single PW with normal incidence to reconstruct low-quality input images. Reference images were reconstructed from the complete set of SA acquisitions. The training of the CNN was performed using a simulated-image dataset with relevant statistical properties, in particular spanning a wide dynamic range. Special attention was given to speckle patterns as they are essential to most displacement estimation techniques deployed in ultrafast US applications. Extensive quantitative evaluations were performed on a numerical test phantom inspired by, and robustness to experimental data was evaluated in both in vitro and in vivo settings. Current limitations and directions for future improvements are discussed. Supplementary Material is also provided, including in-depth statistical and mathematical derivations of concepts involved in the proposed method, extensive experiments performed for hyperparameter search, and additional results obtained. Data and code are available online.

1.2 PROJECT DOMAIN – MACHINE LEARNING

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning techniques and algorithms focus on the development of computer systems that can easily access data and make it readily available for using it for improvement.

1.3 MACHINE LEARNING METHODS

Machine learning algorithms have been categorized into two main subcategories- supervised and unsupervised. Supervised algorithms require supervision by someone who has machine learning skills to provide input and receive the desired output. In addition to that, he/she will be involved in furnishing feedback about the accuracy. Once the model training is complete, the algorithm will be applied to new data.

Unsupervised algorithms do not require any training with the data. However, they do make use of an iterative approach. This approach is called Deep Learning.

Unsupervised learning algorithms are also referred to as neural networks. These networks are used wherever the complexity is more and can perform more tasks than supervised learning systems. These neural networks progress by combing through Dataset for training and automatically identify correlations between variables present in the dataset. Once the model is trained, the algorithm can then use its associations to test the data.

- Supervised machine learning algorithms are applied to the previously studied data in the past and then to new data. Such a system is able to provide outputs for any new input once sufficient training is done. This algorithm also compares its output with the correct, intended output and finds discrepancies, and then modifies the model accordingly.
- On the other hand, unsupervised machine learning algorithms have been when the information has neither been classified nor labeled. This category studies how systems can make inferences into a function that describes a hidden structure in unlabelled data. But there is a drawback, this system doesn't tell the right output, rather it explores the data and draws inferences from datasets.
- Semi-supervised machine learning algorithms lie in between the above-mentioned systems. This is because they use both labelled and unlabelled data for training purposes –a smaller amount of labelled data and a larger amount of unlabelled data in combination. This system uses techniques that are able to improve accuracy. Generally, semi-supervised learning opted when the acquired dataset (labelled) requires skilled resources to train it.
- Reinforcement machine learning algorithms are a learning technique that interacts with the environment. It is done by producing actions and then finding discrepancies. This method allows machines and software agents to contextually compute behavioural patterns in the dataset in order to maximize its performance. Simple reward feedback is then analyzed in order to conclude

which action is the best. The mentioned process is known as the reinforced signal.

1.4 IMAGE PRE-PROCESSING

In imaging sciences, picture processing is the maximum vital part of the process. Most strategies require treating the picture as a two-dimensional sign after which popular sign processing strategies are implemented to it. However, snapshots also can be processed as third-dimensional indicators wherein the 1/3 size is time and it will become the z-axis. Image processing is achieved for virtual snapshots, however, also can be achieved for optical and analogous snapshots. This paper discusses a few fashionable strategies that may be implemented in all of them. The series of snapshots is thought of as 'imaging'. It is carefully associated with pc pictures and vision. In pc pictures, enter snapshots need to be made manually from bodily models. Whereas in pc vision, high-stage picture processing targets to decipher the bodily contents of a picture. Images have also gained scopes due to the growing vitality of scientific visualization. Image analysis caters to the extraction of information using images. This information is mainly from the digital ones. Analysis tasks can be made as simple as barcoding. But at the same time, they can be as sophisticated as the identification of an individual from his/her face. The human visual cortex is an outstanding image analysis apparatus, especially if you wish to extract high-level features.

For this particular reason, several important image analysis tools like edge detectors as well as neural networks have been greatly inspired by the existing human visual perception models. Image editing includes the process of tempering the images. When a traditional image (analog image) is edited, the process is called "Photo Retouching". A lot of image editing software is also used to create computer art from the very beginning. Raster images are initially stored in a computer and that too in the form of a grid, or sometimes in pixels. These pixels actually encompass the information about the colour and brightness.

Images have additionally won scopes because of the developing energy of medical visualization. Image evaluation caters to the extraction of facts the use of photos. This facts is in particular from the virtual ones. Analysis obligations may be made as easy as barcoding. But on the identical time, they may be as state-of-the-art because the identity of an character from his/her face. The human visible cortex is an great picture evaluation apparatus, particularly if you want to extract high-stage features. For this precise reason, numerous essential picture evaluation gear like aspect detectors in addition to neural networks had been significantly stimulated with the aid of using the present human visible belief models. Image enhancing consists of the method of tempering the photos. When a conventional picture (analog picture) is edited, the method is called "Photo Retouching". A lot of picture enhancing software program is likewise used to create pc artwork from the very beginning. Raster photos are first of all saved in a pc and that too withinside the shape of a grid, or every now and then in pixels. These pixels clearly embody the facts approximately the color and brightness.

Image editors may also then alternate the pixels for you to beautify the picture. Several photographs packages had been made able to merging character photos right into a unmarried file. Their orientation and site also can be controlled. When you're deciding on a raster picture, it calls for the separation of edges from the historical past, if it changed into now no longer square in shape. This is noted as "silhouetting".

Another technique to silhouette an picture is to apply clipping paths. Moving similarly down the method, alpha compositing may be finished for gentle translucent edges at the same time as you're deciding on photos. Other than that, there are numerous extra methods to silhouette an picture. Here, the historical past picture is used as a backside layer, and the picture that needs to be blanketed is positioned in any other layer gift above. While the use of a picture layer mask, all components are hidden besides for those which are to be merged. This offers the proper impact of brought components.

1.5 STEPS OF IMAGE PROCESSING

Image Acquisition

This is step one or method of the essential steps of virtual photograph processing. Image acquisition may be as easy as being given a photograph this is already in virtual form. Generally, the photograph acquisition level includes pre-processing, which includes scaling, etc.

Image Enhancement

Image enhancement is many of the only and maximum attractive regions of virtual photo processing. Basically, the concept in the back of enhancement strategies is to deliver out an element this is obscured, or clearly to spotlight positive features in a photo. Such as converting brightness & contrast etc.

Image Restoration

Image recovery is a place that still offers to enhance a photo. However, not unlike enhancement, that's subjective, photo recovery is objective, withinside the experience that recovery strategies have a tendency to be primarily based totally on mathematical or probabilistic fashions of photodegradation.

Colour Image Processing

Colour photograph processing is an area that has been gaining significance due to the good-sized boom withinside the use of virtual pics over the Internet. This may also encompass colour modelling and processing in a virtual area etc.

Wavelets are the muse for representing pics in diverse stages of resolution. Images subdivision successively into smaller areas for facts compression and for pyramidal illustration.

Compression

Compression offers strategies for decreasing the garage required to keep a photograph or the bandwidth to transmit it. Particularly withinside the makes use of the internet, it's miles very a good deal vital to compress facts.

Morphological Processing

Morphological processing offers equipment for extracting photograph additives that are beneficial withinside the illustration and outline of the shape.

Segmentation

In computer vision, photo segmentation is the system of partitioning a virtual photo into a couple of segments. The intention of segmentation is to simplify and/or extrude the illustration of a photo into something this is greater significant and less difficult to analyze. Image segmentation is commonly used to discover gadgets and boundaries (lines, curves, etc.) in images. More precisely, photo segmentation is the system of assigning a label to each pixel in a photo such that pixels with identical label proportion sure characteristics. The end result of photo segmentation is fixed segments that together cowl the complete photo or a fixed of contours extracted from the photo (see side detection). Each of the pixels in an area is comparable with recognition to a few features or computed properties, including shade, intensity, or texture. Adjacent areas are appreciably special with recognition to the identical feature(s). When implemented to a stack of images, usually in scientific imaging, the ensuing contours after photo segmentation may be used to create 3-D reconstructions with the assistance of interpolation algorithms like marching cubes. Segmentation is the maximum crucial component in photo processing. Fence off a whole photo into numerous components that's something greater significant and less difficult for a similar system. These numerous components which can be rejoined will cowl the complete photo. Segmentation might also depend upon numerous capabilities which can be contained withinside the photo. It can be both shade or texture. Before denoising a photo, it's miles segmented to get better the unique photo. The foremost motto of segmentation is to lessen the facts for clean analysis. Segmentation is likewise beneficial in Image Analysis and Image Compression. Segmentation can be classified as follows:

- Region Based
- Edge Based

- Threshold
- Feature-Based Clustering
- Model-Based

a) Region-Based:

In this method pixels that might be associated with an item are grouped for segmentation. The thresholding method is certain with location-primarily based totally segmentation. The location this is detected for segmentation has to be closed. Region-primarily based totally segmentation is likewise termed "Similarity-Based Segmentation". There won't be any holes because of lacking aspect pixels on this location-primarily based on total segmentation. The barriers are diagnosed for segmentation. In every and each step at least one pixel is associated with the location and is taken into consideration. After figuring out the extrude withinside the color and texture, the brink glide is transformed right into a vector. From this, the rims are detected for addition segmentation.

b) Edge Based

Segmentation also can be carried out via way of means of the use of part detection techniques. In this approach, the boundary is diagnosed as to phase. Edges are detected to discover the discontinuities withinside the photograph. Edges at the place are tracked via way of means of figuring out the pixel price and its miles in comparison with the neighboring pixels. For this classification, they use each constant and adaptive capability of the Support Vector Machine (SVM). In this part primarily based totally segmentation, there may be no want for the detected edges to be closed. There are diverse part detectors that are used to phase the photograph. In that Canny part, the detector has a few grades by grade systems for segmentation, that is as follows:

1. To lessen the impact of noise, the floor of the photograph is smoothened via way of means of the use of Gaussian Convolution.
2. Sobel operator is implemented to the photograph to locate the threshold electricity and part instructions.

3. The part instructions are taken into the issue for non-maximal suppression i.e., the pixels that aren't associated with the rims are detected after which, they're minimized.

4. Final step is disposing of the damaged edges i.e., the edge price of a photograph is calculated after which the pixel price is in comparison with the edge this is obtained. If the pixel price is excessive then the edge then, it's miles taken into consideration as a part otherwise it's miles rejected.

c) Threshold:

Thresholding is the easiest way of segmentation. It is done through threshold values which are obtained from the histogram of those edges of the original image. The threshold values are obtained from the edge detected image. So, if the edge detections are accurate then the threshold too. Segmentation through thresholding has fewer computations compared to other techniques. Segmentation is based on "his ton". For a particular segment, there may be a set of pixels which is termed as "his ton". Roughness measure is followed by a thresholding method for image segmentation. Segmentation is done through adaptive thresholding. The gray level points where the gradient is high are then added to the thresholding surface for segmentation. The drawback of this segmentation technique is that it is not suitable for complex images.

1.6 CLASSIFICATION

The reason for the class manner is to categorize all pixels in a virtual photo into one in all numerous land cowl lessons, or "themes". These categorized statistics may also then be used to supply thematic maps of the land cowl found in a photo. Normally, multispectral statistics are used to carry out the class and, indeed, the spectral sample gift in the statistics for every pixel is used because of the numerical foundation for categorization. The goal of photo class is to pick out and portray, as a completely unique grey level (or color), the capabilities going on in a photo in phrases of the item or form of land cowl those capabilities without a doubt constitute the ground. Image class is possibly the maximum crucial part of virtual photo analysis. It may be very quality to have a

"quiet picture" or a photo, displaying the importance of colors illustrating numerous capabilities of the underlying terrain, however, it's far pretty vain until to recognize what the colors simply. (PCI, 1997). Two principal class strategies are Supervised Classification and Unsupervised Classification.

Supervised Classification

With supervised class, we pick out examples of the Information lessons (i.e., land cover type) of hobby within the photo. These are called "schooling sites". The photo processing software program machine is then used to broaden a statistical characterization of the reflectance for every data elegance. This level is frequently called "signature analysis" and might contain growing a characterization as easy because they imply the variety of reflectance on every band, or as complicated as unique analyses of the implied variances and covariance over all bands. Once a statistical characterization has been accomplished for every data elegance, the photo is then categorized via way of means of inspecting the reflectance for every pixel and you make a decision approximately which of the signatures it resembles maximum.

Maximum probability Classification

It is a statistical selection criterion to help within the class of overlapping signatures; pixels are assigned to the elegance of maximum probability. The most probability classifier is taken into consideration to provide extra correct consequences than the parallelepiped class but it's far lots slower because of greater computations.

Minimum distance Classification

Minimum distance classifies photo information on a database document with the use of a fixed of 256 viable magnificence signature segments as unique with the aid of using the signature parameter. Each phase is unique within the signature, for example, shop signature information bearing on a specific magnificence. Only the implied vector in every magnificence signature phrase is used. Other information, inclusive of widespread deviations and covariance matrices, is ignored (even though the most probability classifier makes use of this). A subject matter map encodes every magnificence with a completely

unique grey stage. The grey-stage price used to encode a category is unique whilst the magnificence signature is created. If the subject matter map is later transferred to the display, then a pseudo-colouration desk ought to be loaded in order that every magnificence is represented with the aid of using an exceptional colouration.

Unsupervised Classification

The unsupervised category is a way that examines a big quantity of unknown pixels and divides them into s of the classes primarily based totally on herbal groupings gift withinside the photo values. in contrast to the supervised category, the unsupervised category does now no longer requires analyst-unique schooling information. The fundamental premise is that values inside a given cowl kind ought to be near collectively withinside the dimension space (i.e. have comparable grey levels).The instructions that end result from unsupervised category are spectrally classed which primarily based totally on herbal groupings of the photo values, the identification of the spectral magnificence will now no longer be to start with known, need to examine categorized information to a few form of reference information (inclusive of large scale imagery, maps, or web page visits) to decide the identification and informational values of the spectral instructions. Thus, withinside the supervised method, to outline beneficial records classes after which observe their spectral separability; withinside the unsupervised method, the pc determines spectrally separable magnificence, after which outline their records price.

1.7 COMPARING WITH OTHER RECONSTRUCTION METHODS

CNN-based image reconstruction has several advantages over other image reconstruction techniques such as Fourier-based methods, time-domain methods, and compressed sensing. Fourier-based methods have limitations such as high computational complexity and limited accuracy, while time-domain methods suffer from low signal-to-noise ratios and artifacts.. CNN-based image reconstruction, on the other hand, can handle noisy and corrupted data and can generate high-quality images even from low-quality data.

CHAPTER 2

LITERATURE SURVEY

Thanh Xuan Luong, Bo-Kyeong Kim, et.al (2014) In this paper, it explores the ability of NMF to handle color images. Especially, a new method using NMF to learn features in CNN is proposed. In our experiments conducted on CIFAR10, NMF shows the feasibility for reconstruction and classification of color images. Furthermore, unlike edge- or curve- shaped features learned by AE and RBM in CNN, our method provides dot- shaped features. These new types of features could be considered as basic building blocks in the lowest level of constructing images. Our results demonstrate that NMF is capable of being a supporting tool for CNN in learning features. NMF and nsNMF are capable of being a supporting tool for CNN in learning the features and classifying image data. Though edge- or curve-shaped features have been shown in previous works using AE or RBM, new type of dotshaped features are drawn in our work. our proposed model is applied to one dataset with limited numbers of features. However, there is a room for improving classification performance in future works by applying a better NMF model, such as stacked NMF, to CNN or multi-layer CNN.

Olivier Bernard et.al (2014) infers that Ultrafast imaging based on plane-wave (PW) has become an intense area of research thanks to its capability of reaching frame rate higher than a thousand of frames per second. Several proposed approaches are based on Fourier-domain reconstruction. In these techniques, the Fourier transform of the received echoes is projected to the k-space corresponding to the Fourier transform of the object function. For one emitted PW, N lines along the kz axis direction are reconstructed in the k-space. Propose in this study a new acquisition scheme which allows acquiring the non-null part of the ultrasound spectrum with finer resolution. We show that this strategy allows obtaining images with slightly better lateral resolution and higher contrast-to-noise ratio (CNR) when compared to other Fourier-based techniques. In this paper, this paper proposes a new ultrasound

acquisition scheme based on Fourier slice imaging. This technique allows acquiring the non-null part of the ultrasound spectrum with finer lateral resolution thanks to a dedicated scheme. The quality and improvement of the reconstructed images were investigated through the measurements of spatial resolution and CNR values from numerical simulations and experimental data. In each case, the proposed method yields better results when compared to the others Fourier-based method.

Rafael E. Carrillo, Adrien Besson, et.al (2015) concludes that Ultrafast imaging based on plane-wave (PW) insonification is an active area of research due to its capability of reaching high frame rates. Several approaches have been proposed either based on either of Fourier-domain reconstruction or on delay-and-sum (DAS) reconstruction. Using a single PW, these techniques achieve low quality, in terms of resolution and contrast, compared to the classic DAS method with focused beams. To overcome this drawback, compounding of several steered PWs is needed, which currently decreases the high frame rate limit that could be reached by such techniques. Based on a compressed sensing (CS) framework, propose a new method that allows the reconstruction of high quality ultrasound (US) images from only 1 PW at the expense of augmenting the computational complexity at the reconstruction. In this paper, a novel approach for Fourier-based beamforming is proposed. Exploiting sparsity of US images in a Sparsity averaging model, it allows to recover high quality images using l1-minimization algorithm. This leads to an increase of the CNR of approximately 2dB compared to all the Fourierbased and Space-based techniques for 1 insonifications, while keeping the same spatial resolution. It also enables same contrast as classical DAS method with only 5 PWs. However, the price to pay is a higher computational cost during the reconstruction since solving the l1 minimization problem involves an iterative algorithm.

Shun Miao, et.al (2016) In this paper, it present a Convolutional Neural Network (CNN) regression approach to address the two major limitations of existing intensity-based 2-D/3-D registration technology: 1) slow computation

and 2) small capture range. The CNN regressors are then trained for local zones and applied in a hierarchical manner to break down the complex regression task into multiple simpler sub-tasks that can be learned separately. Weight sharing is furthermore employed in the CNN regression model to reduce the memory footprint. The proposed approach has been quantitatively evaluated on 3 potential clinical applications, demonstrating its significant advantage in providing highly accurate real-time 2-D/3-D registration with a significantly enlarged capture range when compared to intensity-based methods. The results show that PEHL is more accurate and robust than two accelerated intensity-based 2-D/3-D registration methods, Sparse Histogramming MI (SHMI) [9] and Direct Splatting Correlation (DSC) [12], which employ sub-sampled DRR and splatting DRR to quickly compute approximated MI and CC, respectively.

Adrien Besson, Miaomiao Zhang, et.al (2016) infers that Ultrafast imaging based on plane-wave (PW) insonification is an active area of research due to its capability of reaching high frame rates. The framework takes advantage of both the ability to formulate the imaging inverse problem in the Fourier domain and the sparsity of US images in a sparsifying domain. We show, by means of simulations, in vitro and in vivo data, that the proposed framework significantly reduces image artifacts, i.e., measurement noise and sidelobes, compared with classical methods, leading to an increase of the image quality. In this paper, a novel framework for Fourier-based reconstruction of signals obtained with several PW insonifications has been proposed. The framework relies on the ability to pose the Fourier reconstruction problem as an ill-posed inverse problem and on the sparsity of the US images in an analysis domain. The reconstruction is achieved by solving an l_1 -minimization problem.

Adrien Besson, Rafael, et.al (2016) Describe two applications of the framework namely the sparse inversion of the beamforming problem and the compressed beamforming in which the framework is combined with compressed sensing. Based on numerical simulations and experimental

studies, we show the advantage of the proposed methods in terms of image quality compared to classical methods. Two main applications follow on from this formulation. First it enables to increase the image quality by removing measurement artifacts induced by the gridding operation. Secondly, it is suitable to the CS framework and enables the reconstruction of high quality images from undersampled raw data acquired using only a few transducers.

Yang Zhang, Yuexin Guo, et.al (2016) infers that new methodology has been proposed that achieves high contrast and reduces the axial ghost artifact with only three transmissions for ultrafast imaging. A new coherence-based factor was derived. The raw data from the PW and the spherical wave (SW) transmissions were compounded based on the factor, with the consideration of their respective coherence and interrelationship, to suppress the side lobes and reduce the axial artifact. Field II simulations show that our proposed method greatly reduced the axial artifact by 20 dB~35 dB compared with coherent plane wave compounding (CPW) and suppressed side lobes by 15 dB~30 dB compared with CPW and sparse SA imaging. we demonstrated the feasibility of the combined PW and SW transmissions with cross coherence based reconstruction in reducing the axial ghost artifact and side lobes in ultrafast imaging. Based on the analysis of axial artifacts and side lobes, proposed method reduce the axial artifacts by 20dB ~ 35 dB, and suppress the side lobes 15dB ~ 30dB. One of the limitations of this work is the weak energy of the SW transmissions by the leftmost and rightmost elements. Since only one element was used to generate a SW, the signal would be affected by the noise in the deep region of interest in the scanned medium. Future work consists in replacing the SW transmissions by diverging wave transmissions.

Li Fangmin, Chen Ke, et.al, (2017) infers that Using CNN to regress 3DMM shape and texture parameters directly from an input photo and offering a method for generating huge numbers of labeled examples. There are two key points of the paper: one is the training data generation for the model training; the other is the training of 3D reconstruction model. Experimental results and analysis show that this method costs much less time than

traditional methods of 3D face modeling, and it is improved for different races on photos with any angles than the existing methods based on deep learning, and the system has better robustness. It proposes instead to use a very deep CNN architecture to regress 3DMM parameters directly from input images. We provide a low-cost solution to the problem of obtaining sufficient labeled data to train this network. It shows our regressed 3D shapes to be more accurate and robust than those of alternative methods.

Rinan Wei, Fugen Zhou, et.al, (2017) In this work, a volumetric imaging method from one X-ray projection utilizing convolutional neural network (CNN) is proposed. With the aid of principal component analysis (PCA)-based motion model, a CNN regression model with weighted object function is trained to estimate the volumetric image accurately. Due to the high parallelization of CNN, the computing efficiency of the proposed method is able to meet the real-time requirement of practical treatment (less than 0.05 seconds). A synthetic test using 4D Extended Cardiac-Torso (XCAT) Phantom is carried out which testify the effectiveness of our method. In this paper, we developed a new volumetric imaging method from single projection based on CNN. PCA motion model is applied as prior information for the estimation of volumetric image.

Harshit Gupta, Kyong Hwan Jin, et.al, (2018) In this paper a new image reconstruction method that replaces the projector in a projected gradient descent (PGD) with a convolutional neural network (CNN). It proposes a relaxed version of PGD wherein gradient descent enforces measurement consistency, while a CNN recursively projects the solution closer to the space of desired reconstruction images. It show that this algorithm is guaranteed to converge and, under certain conditions, converges to a local minimum of a non-convex inverse problem. Finally, we propose a simple scheme to train the CNN to act like a projector. The proposed framework is generic and can be used to solve a variety of inverse problems including superresolution, deconvolution, accelerated MRI, etc. This can bring more robustness and reliability to the current deep-learning-based techniques.

Zixia Zhou, Yuanyuan Wang, et.al, (2018) A novel convolutional neural network (CNN) model for the high spatial–temporal resolution reconstruction of PW ultrasound images is proposed in this paper. Considering the multiangle form of PW data, a multichannel model is introduced to produce balanced training. To combine local and contextual information, the multiscale model is adopted. These two innovations constitute our multichannel and multiscale CNN (MMCNN) model. The advantages of our proposed method were compared with a coherent PW compounding method, a conventional maximum a posteriori-based high spatial resolution reconstruction method, and a 2-D CNN compounding method, and the results verified that our approach is capable of attaining a better temporal resolution and comparable spatial resolution. The proposed approach facilitates the generation of ultrasound images with appropriate spatial and temporal resolution, and the experimental results show its superiority from both subjective and objective perspectives. The proposed method has the potential to be applied to many ultrafast imaging applications.

Jorge Racedo and Matthew W. Urban, et.al, (2019) The proposed method uses multiple focused ultrasound beams to generate push beams with acoustic radiation force. Applying these push beams generates propagating shear waves. The propagation motion is measured with ultrafast ultrasound imaging. The shear wave motion data are directionally filtered, and a 2-D shear wave velocity (SWV) algorithm is applied to create group velocity maps. This algorithm uses a moving window and a specified patch for performing cross-correlations of time-domain signals. This study presented a systematic evaluation of a 2-D SWV analysis to determine the effects of varying patch (p) and window (w) sizes has on various image evaluation metrics. It was found that large values for p and w provided reliable measurements of SWV in homogeneous phantoms with low CV. For the inclusion phantoms, different trends for the p and w values for optimizing CNR and bias. This type of study provides a framework for constructing optimal images that could be reconstruction using an iterative or multiscale approach.

Jingfeng Lu, Fabien Millioz, et.al (2019) This work proposes a convolutional neural network (CNN) architecture for high-quality reconstruction of DW ultrasound images using a small number of transmissions. Experimentally it is demonstrated that the proposed method produces high-quality images using only three DWs, yielding an image quality equivalent to the one obtained with standard compounding of 31 DWs in terms of contrast and resolution. A deep-learning-based method is presented in this work for the reconstruction of diverging wave imaging. The proposed approach aims at learning a compounding operator to reconstruct high-quality images using a small number of DWs. The experiments are performed using a large number in vitro and in vivo samples. The experimental results demonstrated the effectiveness of the proposed method, producing an image quality equivalent to the one obtained with standard compounding of 31DWs in terms of contrast and resolution.

Anny Yuniarti, Nanik Suciati, et.al, (2020) In this paper, we implemented several deep-learning models to decode the ShapeNet rendering images that contain 13 model categories to examine the various hyper-parameters' impacts on each 3D model category. Our experiments showed that the hyper-parameters of the learning rate and epochs set to either 0.001 or 0.0001 and 60-80 epochs significantly outperformed other settings. After the tuning of the hyper-parameters was thoroughly investigated, this study also incorporated multiple architectures for further validation. Moreover, analysis of the network performance also was performed on the category wise level. Moreover, it observed that regardless of network configuration, some categories (plane, watercraft, car) performed better throughout the study. Therefore, a 3D reconstruction based on image classification can be designed based on the best performing categories.

Dimitris Perdios, Manuel Vonlanthen, et.al, (2020) In this work, investigated the applicability of convolutional neural network (CNN)-based image reconstruction, having recently proven its potential in reducing GL artifacts, for reconstructing images from single unfocused acquisitions using

uniformly undersampled linear array configurations on receive. The proposed reconstruction method consists of first computing a low-quality estimate from the undersampled single-shot acquisitions using a delay-and-sum (DAS) algorithm, followed by applying a real-time-capable CNN, trained specifically to reduce diffraction artifacts. The proposed approach achieved an image comparable or better to that obtained from conventional DAS beamforming using the full array with uniformly undersampled arrays up to a factor of three, demonstrating a promising potential for sparse array imaging in general. the proposed CNN-based image reconstruction method can increase the image quality achieved from single PW acquisitions using uniformly undersampled linear arrays on receive. Indeed, the overall quality of the restored images is competitive to images reconstructed by a DAS algorithm from single PW acquisitions on the full array up to an undersampling factor of three, demonstrating a high potential in the context of sparse array imaging.

Dimitris Perdios, et.al, (2021) The proposed approach relies on single ultrafast acquisitions to reconstruct high-quality frames and on only two consecutive frames to obtain 2-D displacement estimates. To this end, we deployed a convolutional neural network-based image reconstruction method combined with a speckle tracking algorithm based on cross-correlation. This approach is capable of estimating displacements in regions where the presence of side lobe and grating lobe artifacts prevents any displacement estimation with a state-of-the-art technique that relies on conventional delay-and-sum beamforming. The approach consists of a CNN trained to restore high-quality images from single unfocused acquisitions and a speckle tracking algorithm to estimate inter-frame displacements from two consecutive frames only. The proposed approach may therefore unlock the full potential of ultrafast ultrasound, in applications such as ultrasensitive cardiovascular motion and flow analysis or shear-wave elastography.

Shohei Ouchi and Satoshi, et.al, (2021) In this study, proposed a novel Transformed Image Domain CNN-CS using multi-channel grouped CNN-based image reconstruction using the Fresnel transform (eFREBAS

transform). Experimental results showed that the proposed method was able to predict an artifact-free image better than other methods, especially for a 20-30% low sampling rate. eFREBAS-CNN enables us to remove most of aliasing artifacts and improves the restoration of the fine structure of images. These results indicate that the application transformed image domain-based CNN-CS is effective in upgrading reconstruction performance.

Regev Cohen, et.al, (2021) The proposed technique considers diverging-wave transmission and achieves improved image resolution and contrast compared with standard delay-and-sum beamforming while enabling a high frame rate. Incorporating 2-D sparse arrays into our method creates SCOPA-3D: a sparse beamformer that offers significant element reduction and, thus, allows performing 3-D imaging with the resources typically available for 2-D setups. To create 2-D thinned arrays, we present a scalable and systematic way to design 2-D fractal sparse arrays. Fractal array design complements the proposed beamforming by allowing us to construct sparse arrays where the majority of receive electronics are discarded. Thus, we reduce the processing rate, cost, and power, facilitating the use of high-performance 3-D US imaging with limited hardware. The proposed framework paves the way for affordable ultrafast US devices that perform high-quality 3-D imaging, as demonstrated using phantom and ex-vivo data.

Jui-Ying Lu, Po-Yang Lee, et.al, (2022) In this study, a convolutional neural network (CNN) beamformer based on a combination of the GoogLeNet and U-Net architectures was developed to replace the conventional delay-and-sum (DAS) algorithm to obtain high-quality images at a high frame rate. RF channel data are used as the inputs for the CNN beamformers. The outputs are in-phase and quadrature data. Simulations and phantom experiments revealed that the images predicted by the CNN beamformers had higher resolution and contrast than those predicted by conventional single-angle PW imaging with the DAS approach. In in vivo studies, the contrast-to-noise ratios (CNRs) of carotid artery images predicted by the CNN beamformers using three or five PWs as ground truths were approximately 12 dB in the transverse

view, considerably higher than the CNR obtained using the DAS beamformer (3.9 dB). Most tissue speckle information was retained in the in vivo images produced by the CNN beamformers. In conclusion, only a single PW at 0° was fired, but the quality of the output image was proximal to that of an image generated using three or five PW angles. The quality–frame rate tradeoff of coherence compounding could be mitigated through the use of the proposed CNN for beamforming.

Luchies A, Van der Schoot, et.al (2020) In this paper it provides a comprehensive review of the current state-of-the-art in deep learning-based approaches for ultrafast ultrasound imaging. The authors discuss various deep learning architectures that have been proposed for ultrafast ultrasound imaging, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs). The paper also provides a detailed overview of the datasets used for training and validating these deep learning models, as well as the metrics used for evaluating their performance. The authors highlight the potential of these deep learning-based approaches to improve the accuracy and efficiency of ultrasound imaging, particularly in clinical applications such as obstetrics, cardiology, and oncology. The paper concludes with a discussion of future research directions in this area, including the integration of other imaging modalities and the development of more sophisticated deep learning architectures.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

VGG 19

The existing system uses VGG 19. A fixed size of (224 * 224) RGB image was given as input to this network which means that the matrix was of shape (224,224,3).The only preprocessing that was done is that they subtracted the mean RGB value from each pixel, computed over the whole training set. Used kernels of (3 * 3) size with a stride size of 1 pixel, this enabled them to cover the whole notion of the image.Spatial padding was used to preserve the spatial

resolution of the image. Max pooling was performed over a 2×2 pixel windows with stride 2. This was followed by Rectified linear unit (ReLU) to introduce non-linearity to make the model classify better and to improve computational time as the previous models used tanh or sigmoid functions this proved much better than those. Implemented three fully connected layers from which first two were of size 4096 and after that a layer with 1000 channels and the final layer is a softmax function.

2.3 PROBLEM STATEMENT

The main problem that we are trying to solve is the inefficient methods proposed by the existing system and also the misclassification of the outputs. Also the dataset that was used was inaccurate and improper.

CHAPTER 3

AIM AND SCOPE OF THE PRESENT INVESTIGATION

3.1 AIM OF THE INVESTIGATION

The aim of CNN-based image reconstruction for ultrafast ultrasound imaging is to develop a deep learning-based approach that can provide high-quality images with high temporal resolution. This approach involves training a convolutional neural network (CNN) using a large dataset of ultrasound images and corresponding high-quality images to generate real-time, high-quality ultrasound images with reduced radiation exposure and improved accuracy in clinical applications such as cardiology and obstetrics.

Ultrafast ultrasonic imaging refers to the acquisition of a large number of ultrasound frames in a short period of time, which can enable imaging of fast-moving structures such as blood flow and tissue motion. However, the large amount of data generated by ultrafast imaging can be challenging to process and reconstruct into a coherent image.

CNN-based approaches aim to address this challenge by leveraging the power of deep learning to learn the underlying patterns in the raw ultrasound data and use this information to reconstruct high-quality images. By training CNN models on large datasets of ultrasound images, these approaches can learn to recognize and extract features that are relevant to the imaging task, such as tissue boundaries, blood flow patterns, and other structural details.

The ultimate goal of these image reconstruction methods is to enable clinicians to obtain high-quality images in real-time, which can improve diagnostic accuracy and enable more precise and targeted treatments. By providing better spatial resolution and reduced noise levels, CNN-based approaches can help to overcome some of the limitations of traditional ultrasound imaging techniques and expand the range of applications for ultrasonic imaging in clinical practice.

3.2 SCOPE OF THE INVESTIGATION

The scope of CNN-based image reconstruction for ultrafast ultrasound imaging includes developing new deep learning architectures, optimizing training and validation datasets, and integrating multiple imaging techniques to improve accuracy and efficiency. The approach has potential for clinical applications such as obstetrics, cardiology, oncology, and real-time imaging with reduced radiation exposure.

The future scope of image reconstruction methods for ultrafast ultrasonic imaging based on CNNs is quite promising. CNNs have proven to be effective in various image processing tasks, including image reconstruction. With the increasing availability of large amounts of high-quality data and the continuous improvement of computational resources, CNN-based approaches are expected to provide better results in image reconstruction for ultrafast ultrasonic imaging.

One of the major advantages of CNNs is their ability to learn features from raw data without the need for feature engineering. This can be particularly useful in cases where the features to be extracted are complex and difficult to define manually. Moreover, CNN-based methods are inherently parallelizable, which makes them efficient for processing large datasets.

In addition, the availability of powerful hardware platforms such as GPUs and TPUs has made it possible to train and deploy large-scale CNN models in real-time, which could enable ultrafast image reconstruction for ultrasonic imaging. This could potentially lead to the development of real-time imaging systems that provide high-quality images with minimal latency.

Overall, the future of image reconstruction methods for ultrafast ultrasonic imaging based on CNNs is bright. As the field continues to grow and evolve, we can expect to see further advancements in this area, leading to faster and more accurate imaging techniques for a wide range of applications.

CHAPTER 4

PROPOSED METHODOLOGY

4.1 CNN CLASSIFICATION

The convolutional neural network (CNN) is a class of deep learning neural networks. CNNs represent a huge breakthrough in image recognition. They're most commonly used to analyze visual imagery and are frequently working behind the scenes in image classification. They can be found at the core of everything from facebook's photo tagging to self-driving cars. They're working hard behind the scenes in everything from healthcare to security. Image classification is the process of taking an input (like a picture) and outputting a class or a probability that the input is a particular class ("there's a 90% probability that this input is a image"). CNNs can be thought of automatic feature extractors from the image. It effectively uses adjacent pixel information to effectively down-sample the image. A CNN, in specific, has one or more layers of convolution units.

A convolution unit receives its input from multiple units from the previous layer which together create a proximity. Therefore, the input units (that form a small neighborhood) share their weights. In this project, the input to CNN classification is series of images processed through wavelet transforms. Every image is given as input to neurons in input layer. The software selects smaller matrix also known as filter. The filter produces convolution and multiplies its values by original pixel values. All these multiplications are summed up to obtain a single value. The convolution continues and a smaller matrix than input matrix is obtained. The output matrix of CNN classification is compared with another image matrix (that contains stone) and classification is done.

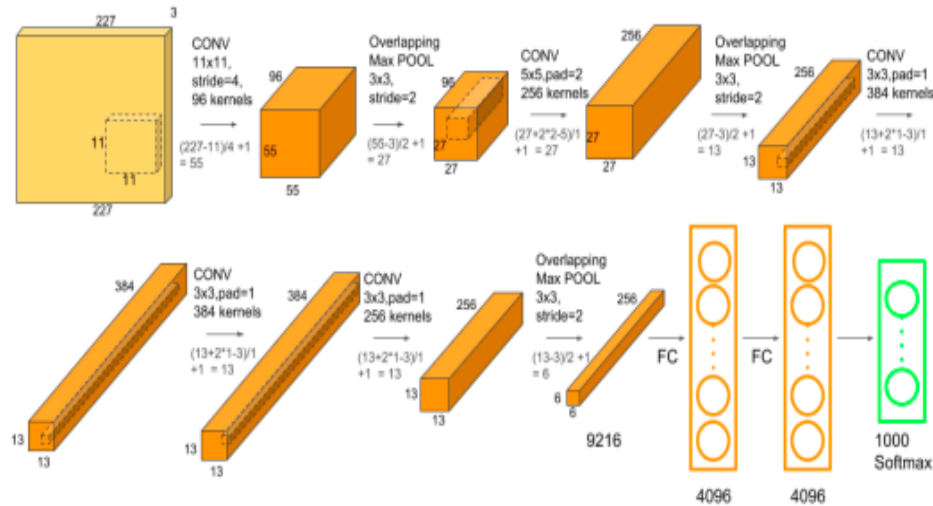


Fig:4.1:CNN Architecture

1. Input: Color images of size 227x227x3
2. Conv-1: The first convolutional layer consists of 96 kernels of size 11x11 applied with a stride of 4 and padding of 0.
3. MaxPool-1: The maxpool layer following Conv-1 consists of pooling size of 3x3 and stride 2.
4. Conv-2: The second conv layer consists of 256 kernels of size 5x5 applied.
5. Conv-2 consists of pooling size of 3x3 and a stride of 2.
6. Conv-3: The third conv layer consists of 384 kernels of size 3x3 applied with a stride of 1 and padding of 1.
7. FC-1: The first fully connected layer has 4096 stride of 1 and padding of 2.
8. MaxPool-2: The maxpool layer following neurons.
9. FC-2: The second fully connected layer has 4096 neurons.
10. FC-3: The third fully connected layer has 1000 neurons.

The size of output image of a Conv Layer

O=size(width) of output image.

I=size(width) of input image.

K=size(width) of kernels used in the Conv layer.

N=number of kernels.

S=stride of the convolution operation.

P=padding.

The size(O) of the output image is given by

$$O = [(I - K + 2P) / S] + 1$$

The no. of channels in the output image is equal to the no. of kernels N.

CNN Classification involves 4 steps namely Convolution layer, Activation function, max Pooling, Fully connected network.

Relu layer: Rectified linear unit is used to scale the parameters to non negative values. We get pixel values as negative values too. In this layer we make them as 0's. The purpose of applying the rectifier function is to increase the non-linearity in our images (fig 4.1.4). The reason we want to do that is that images are naturally non-linear. The rectifier serves to break up the linearity even further in order to make up for the linearity that we might impose an image when we put it through the convolution operation. What the rectifier function does to an image like this is remove all the black elements from it, keeping only those carrying a positive value (the grey and white colors). The essential difference between the non-rectified version of the image and the rectified one is the progression of colors. After we rectify the image, you will find the colors changing more abruptly. The gradual change is no longer there. That indicates that the linearity has been disposed of.

Pooling layer: The pooling layer reduces the height and width of the input. It helps reduce computation, as well as helps make feature detectors more invariant to its position in the input. This process is what provides the convolutional neural network with the “spatial variance” capability (fig 4.1.5). In addition to that, pooling serves to minimize the size of the images as well as the number of parameters which, in turn, prevents an issue of “overfitting” from coming up. Overfitting in a nutshell is when you create an excessively complex model in order to account for the idiosyncracies we just mentioned. The result of using a pooling layer and creating down sampled or pooled feature maps is a summarized version of the features detected in the input. They are useful as small changes in the location of the feature in the input detected by the convolutional layer will result in a pooled feature map with the feature in the

same location. This capability added by pooling is called the model's invariance to local translation.

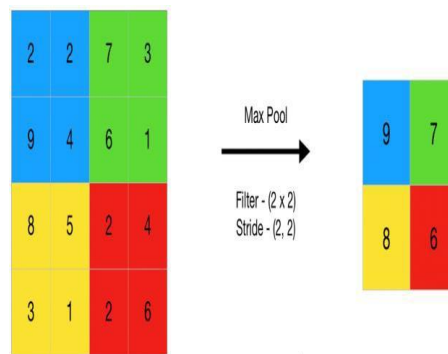


Fig:4.2: Maxpooling

Fully Connected layer: The role of the artificial neural network is to take this data and combine the features into a wider variety of attributes that make the convolutional network more capable of classifying images, which is the whole purpose from creating a convolutional neural network. It has neurons linked to each other, and activates if it identifies patterns and sends signals to output layer. the output layer gives output class based on weight values.

In Convolution layer a 3*3 kernel is applied on the input matrix with stride 1, so that the size of the image is reduced. The obtained matrix is sent to the activation function layer, here ReLU (Rectified Linear Unit) activation function is used to eliminate negative values. The next step is max pooling, here the rectified map goes through a pooling layer, pooling is down sampling operation that reduces the dimensionality of feature map. The output of this layer is a matrix with reduced size containing all the features. These 3 steps are repeated for two times, in which 32 filters are used each time. The next step is Flattering in which we convert the 2D array from pooling into a long continuous linear vector to which a filter of size 64 is applied followed by activation function. Later a Drop Out of size 0.5 is applied to prevent over-fitting. In the next step ANN model is applied, in which sigmoid activation is used function to detect the presence of stone.

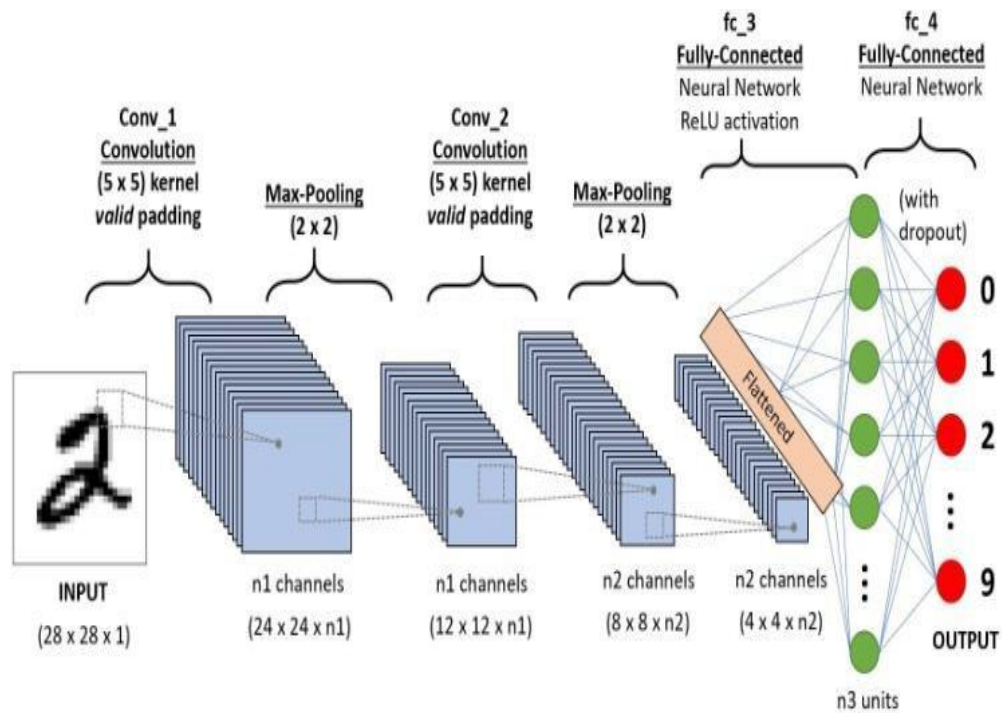


Fig:4.3: Convolution methodology

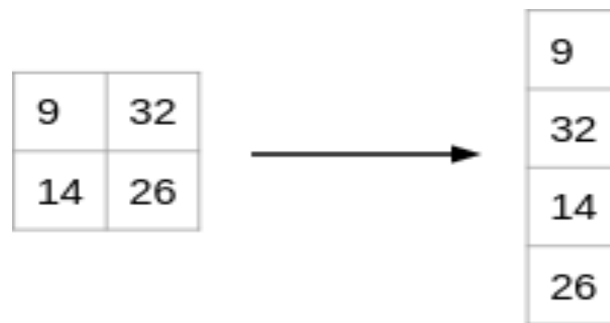


Fig:4.4: Converting matrix into linear array form

CNN works by extracting features from the images. Any CNN consists of the following:

1. The input layer which is a grayscale image
2. The Output layer which is a binary or multi-class labels
3. Hidden layers consisting of convolution layers, ReLU (rectified linear unit) layers, the pooling layers, and a fully connected Neural Network

It is very important to understand that ANN or Artificial Neural Networks, made up of multiple neurons is not capable of extracting features from the image. This is where a combination of convolution and pooling layers comes into the picture. Similarly, the convolution and pooling layers can't perform classification hence we need a fully connected Neural Network.

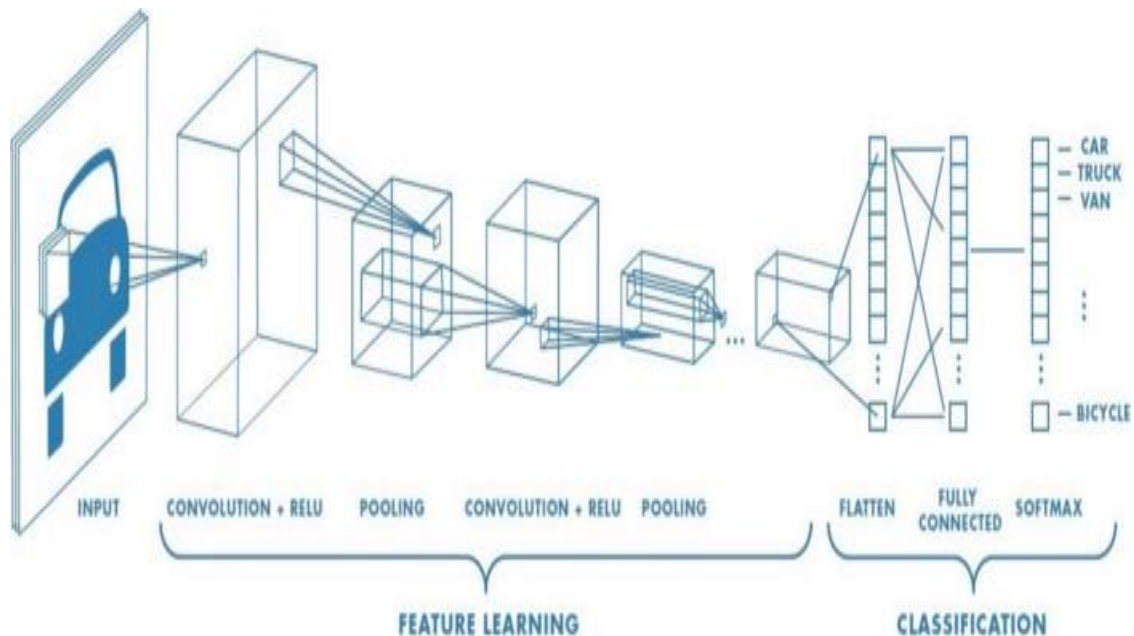


Fig:4.5: CNN process from input to Output Data

Let's consider that we have access to multiple images of different vehicles, each labeled into a truck, car, van, bicycle, etc. Now the idea is to take these pre-label/classified images and develop a machine learning algorithm that is capable of accepting a new vehicle image and classify it into its correct category or label. Now before we start building a neural network we need to understand that most of the images are converted into a grayscale form before they are processed.

4.2 MODULES:

Module 1: Data pre-processing module

Module 2: CNN Module

Module 3: Post-Preprocessing Module

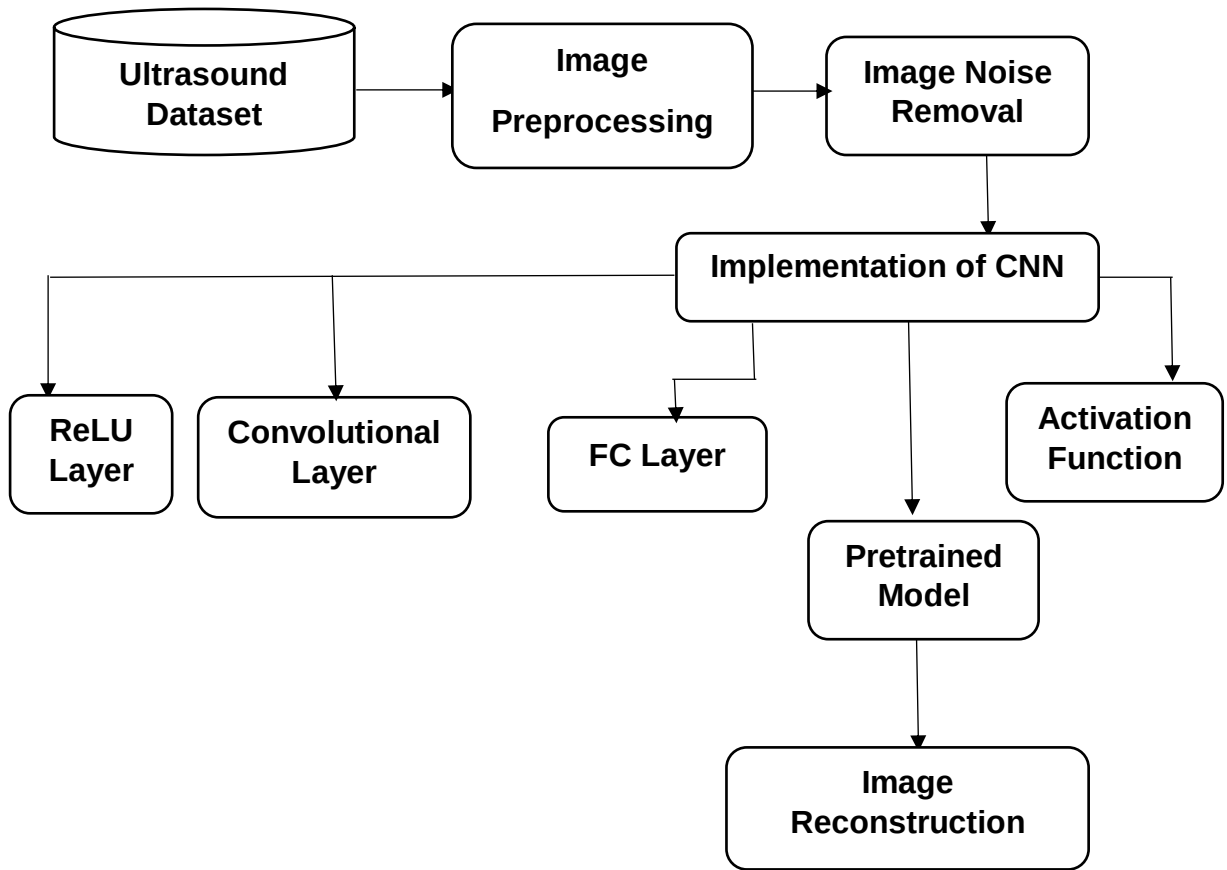


Fig:4.6: Block Diagram of Image Reconstruction

MODULE 1: DATA PRE-PROCESSING

The Data pre-processing module is an important step in CNN-based image reconstruction for ultrafast ultrasound imaging. The main goal of this module is to prepare the acquired ultrasound data for input into the CNN by performing several pre-processing steps. These steps aim to improve the quality of the input data and ensure consistency across the acquired images.

One of the first steps in the Data pre-processing module is image registration. Ultrasound images may be acquired at different angles or positions, which can result in misalignment between images. Image registration is necessary to align the images and ensure consistency in the input data.

Another important step in the Data pre-processing module is noise reduction. Ultrasound images are often affected by noise, which can degrade image quality and reduce the accuracy of the reconstructed images. There are several techniques that can be used to reduce noise in ultrasound images, such as wavelet denoising, median filtering, and Gaussian filtering.

Normalization is another step in the Data pre-processing module that involves scaling the intensity values of the input images to a common range. This is important to ensure that the CNN can learn from the input data and produce accurate output. Normalization techniques may include min-max scaling, z-score normalization, and logarithmic normalization.

In addition to image registration, noise reduction, and normalization, there are other pre-processing steps that may be included in the Data pre-processing module. For example, contrast enhancement techniques can be used to improve the visibility of features in the ultrasound images, such as edge detection and histogram equalization. Pre-processing steps can also be used to remove artifacts from the images, such as speckle noise and motion artifacts.

Once the pre-processing steps are completed, the input data is ready to be fed into the CNN module for training and testing. It is important to note that the specific pre-processing steps used in the Data pre-processing module can vary depending on the application and the type of ultrasound data being used. For example, pre-processing steps may be different for 2D and 3D ultrasound data, or for different types of ultrasound imaging modalities such as B-mode or Doppler imaging.

In summary, the Data pre-processing module for CNN-based image reconstruction for ultrafast ultrasound imaging involves several steps to prepare the acquired ultrasound data for input into the CNN. These steps may include image registration, noise reduction, normalization, and other pre-processing techniques to improve the quality of the input data and ensure consistency across the acquired images.

The specific pre-processing steps used may vary depending on the application and type of ultrasound data being used.

MODULE 2: CNN MODULE

The CNN module is a crucial part of CNN-based image reconstruction for ultrafast ultrasound imaging. This module involves training and implementing the CNN for image reconstruction. The CNN is trained using a large dataset of ultrasound images and corresponding high-quality images, and the trained network is then used to generate high-quality images from the acquired data in real-time.

The CNN module consists of several components, including the input layer, hidden layers, and output layer. The input layer receives the pre-processed ultrasound data, which is then passed through a series of hidden layers. These hidden layers consist of convolutional layers, pooling layers, and activation functions, which are used to extract and learn features from the input data.

Convolutional layers are used to perform convolution operations on the input data, which involve applying a filter to the input data to extract local features. These filters are learned during the training phase and can vary in size and complexity. Pooling layers are used to downsample the output of the convolutional layers, reducing the spatial dimensionality of the data and allowing the network to learn more abstract features. Activation functions are used to introduce non-linearity into the network, allowing it to model complex relationships between the input and output data.

After the hidden layers, the output layer generates the reconstructed ultrasound image. The output layer may consist of one or more fully connected layers, which take the learned features from the hidden layers and generate the final output. The output layer may also use different activation functions, depending on the application and the type of output data being generated.

The CNN module also involves training the network using a large dataset of ultrasound images and corresponding high-quality images. The training

process involves minimizing the difference between the output of the CNN and the ground truth images using a loss function, such as mean squared error or mean absolute error. The training data is typically split into training, validation, and test sets, with the training and validation sets used to optimize the network parameters and the test set used to evaluate the network performance.

Once the CNN is trained, it can be used to generate high-quality ultrasound images in real-time from the acquired ultrasound data. The reconstructed images can be further processed using post-processing techniques to improve image quality and accuracy.

It is important to note that there are several factors that can affect the performance of the CNN module, including the choice of network architecture, the size and quality of the training dataset, and the hyperparameters used during training. These factors need to be carefully optimized to ensure optimal performance of the CNN module.

In summary, the CNN module for CNN-based image reconstruction for ultrafast ultrasound imaging involves training and implementing a CNN for image reconstruction. The module consists of several components, including the input layer, hidden layers, and output layer, and involves using convolutional layers, pooling layers, and activation functions to extract and learn features from the input data. The CNN is trained using a large dataset of ultrasound images and corresponding high-quality images, and the trained network is then used to generate high-quality images from the acquired data in real-time.

MODULE 3: POST-PROCESSING MODULE

The Post-processing module is a crucial step in CNN-based image reconstruction for ultrafast ultrasound imaging. The main goal of this module is to further process the reconstructed images generated by the CNN to improve their quality and accuracy. The Post-processing module is a crucial step in CNN-based image reconstruction for ultrafast ultrasound imaging. The main goal of this module is to further process the reconstructed images generated by the CNN to improve their quality and accuracy. The post-

processing steps may include noise reduction, contrast enhancement, edge detection, and other techniques that can improve image quality and make it easier for clinicians to interpret the images.

One of the first steps in the Post-processing module is noise reduction. Even after the pre-processing and reconstruction steps, the reconstructed images may still contain noise. There are several techniques that can be used to reduce noise in ultrasound images, such as wavelet denoising, median filtering, and Gaussian filtering. These techniques are applied to the reconstructed images to remove any remaining noise and improve image quality.

Contrast enhancement is another important step in the Post-processing module. This involves improving the visibility of the structures in the image by adjusting the contrast and brightness. Techniques such as histogram equalization and adaptive histogram equalization can be used to improve contrast and enhance the visibility of structures in the image.

Edge detection is another technique that can be used in the Post-processing module to improve image quality. Edge detection algorithms can be used to identify the boundaries of structures in the image, making it easier for clinicians to identify specific structures and interpret the image. This technique can be particularly useful in applications such as cardiac imaging and musculoskeletal imaging.

Other post-processing techniques that can be used include texture analysis, feature extraction, and segmentation. Texture analysis can be used to identify patterns and textures in the image, which can provide additional information about the underlying tissue. Feature extraction can be used to extract specific features from the image, such as blood flow velocity or tissue elasticity. Segmentation can be used to separate different structures in the image, such as different organs or tissue types.

It is important to note that the specific post-processing steps used in the Post-processing module can vary depending on the application and the type of ultrasound data being used. For example, different post-processing techniques may be used for 2D and 3D ultrasound data, or for different types of ultrasound imaging modalities such as B-mode or Doppler imaging.

Once the post-processing steps are completed, the final reconstructed image is generated, which can be used for clinical interpretation and diagnosis. The quality of the reconstructed image is critical for accurate diagnosis, so the Post-processing module is an important step in the overall CNN-based image reconstruction process.

In summary, the Post-processing module for CNN-based image reconstruction for ultrafast ultrasound imaging involves several steps to further process the reconstructed images generated by the CNN. The specific post-processing steps used may vary depending on the application and type of ultrasound data being used. The goal of the Post-processing module is to improve the quality and accuracy of the reconstructed images, making them easier to interpret for clinical diagnosis.

A Convolutional neural network (CNN or convnet) is a subset of machine learning. It is one of the various types of artificial neural networks which are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data. There are other types of neural networks in deep learning, but for identifying and recognizing objects, CNNs are the network architecture of choice.

4.3 ADVANTAGES OF PROPOSED SYSTEM

CNN-based image reconstruction for ultrafast ultrasound imaging has several advantages such as:

High-quality images: CNNs can generate high-quality images with low noise and artifacts.

Real-time processing: CNN-based image reconstruction is fast and can provide real-time image reconstruction.

Robustness: CNNs can handle noisy and corrupted data and can generate high-quality images even from low-quality data.

Generalizability: CNNs can generalize to new and unseen data, making them useful in various clinical applications.

4.4 TESTING METHODOLOGIES

There are many different types of testing methods or techniques used as part of the software testing methodology. Some of the important testing methodologies are:

System Testing

Testing is performed to identify errors. It is used for quality assurance. Testing is an integral part of the entire development and maintenance process. The goal of the testing during phase is to verify that the specification has been accurately and completely incorporated into the design, as well as to ensure the correctness of the design itself. For example the design must not have any logic faults in the design is detected before coding commences, otherwise the cost of fixing the faults will be considerably higher as reflected. Detection of design faults can be achieved by means of inspection as well as walkthrough.

Testing is one of the important steps in the software development phase. Testing checks for the errors, as a whole of the project testing involves the following test cases:

- Static analysis is used to investigate the structural properties of the Source code.
- Dynamic testing is used to investigate the behavior of the source code by executing the program on the test data.

Unit Testing

Unit testing is conducted to verify the functional performance of each modular component of the software. Unit testing focuses on the smallest unit

of the software design (i.e.), the module. The white-box testing techniques were heavily employed for unit testing.

Functional Tests

Functional test cases involved exercising the code with nominal input values for which the expected results are known, as well as boundary values and special values, such as logically related inputs, files of identical elements, and empty files.

Three types of tests in Functional test:

- Performance Test
- Stress Test
- Structure Test

Performance Test

It determines the amount of execution time spent in various parts of the unit, program throughput, and response time and device utilization by the program unit.

Stress Test

Stress Test is those tests designed to intentionally break the unit. A Great deal can be learned about the strength and limitations of a program by examining the manner in which a programmer in which a program unit breaks.

Structure Test

Structure Tests are concerned with exercising the internal logic of a program and traversing particular execution paths. The way in which White-Box test strategy was employed to ensure that the test cases could Guarantee that all independent paths within a module have been have been exercised at least once.

- Exercise all logical decisions on their true or false sides.
- Execute all loops at their boundaries and within their operational bounds.
- Exercise internal data structures to assure their validity.
- Checking attributes for their correctness.

- Handling end of file condition, I/O errors, buffer problems and textual errors in output information

Integration Testing

Integration testing is a systematic technique for construction the program structure while at the same time conducting tests to uncover errors associated with interfacing. i.e., integration testing is the complete testing of the set of modules which makes up the product. The objective is to take untested modules and build a program structure tester should identify critical modules. Critical modules should be tested as early as possible. One approach is to wait until all the units have passed testing, and then combine them and then tested. This approach is evolved from unstructured testing of small programs. Another strategy is to construct the product in increments of tested units. A small set of modules are integrated together and tested, to which another module is added and tested in combination. And so on. The advantages of this approach are that, interface dispenses can be easily found and corrected.

The major error that was faced during the project is linking error. When all the modules are combined the link is not set properly with all support files. Then we checked out for interconnection and the links. Errors are localized to the new module and its intercommunications. The product development can be staged, and modules integrated in as they complete unit testing. Testing is completed when the last module is integrated and tested.

4.5 TESTING TECHNIQUES / TESTING STRATEGIES

Testing is a process of executing a program with the intent of finding an error. A good test case is one that has a high probability of finding an as-yet – undiscovered error. A successful test is one that uncovers an as-yet-undiscovered error. System testing is the stage of implementation, which is aimed at ensuring that the system works accurately and efficiently as expected before live operation commences. It verifies that the whole set of programs hang together. System testing requires a test consists of several key activities

and steps for run program, string, system and is important in adopting a successful new system. This is the last chance to detect and correct errors before the system is installed for user acceptance testing.

The software testing process commences once the program is created and the documentation and related data structures are designed. Software testing is essential for correcting errors. Otherwise the program or the project is not said to be complete. Software testing is the critical element of software quality assurance and represents the ultimate the review of specification design and coding.

Testing is the process of executing the program with the intent of finding the error. A good test case design is one that as a probability of finding an yet undiscovered error. A successful test is one that uncovers an yet undiscovered error. Any engineering product can be tested in one of the two ways:

White box testing

This testing is also called as Glass box testing. In this testing, by knowing the specific functions that a product has been design to perform test can be conducted that demonstrate each function is fully operational at the same time searching for errors in each function. It is a test case design method that uses the control structure of the procedural design to derive test cases. Basis path testing is a white box testing.

Basis path testing:

- Flow graph notation
- Cyclometric complexity
- Deriving test cases
- Graph matrices Control

Black box testing

In this testing by knowing the internal operation of a product, test can be conducted to ensure that “all gears mesh”, that is the internal operation performs according to specification and all internal components have been

adequately exercised. It fundamentally focuses on the functional requirements of the software.

The steps involved in black box test case design are:

- Graph based testing methods
- Equivalence partitioning
- Boundary value analysis
- Comparison testing

4.6 SOFTWARE TESTING STRATEGIES:

A software testing strategy provides a road map for the software developer. Testing is a set activity that can be planned in advance and conducted systematically. For this reason a template for software testing a set of steps into which we can place specific test case design methods should be strategy should have the following characteristics:

- Testing begins at the module level and works “outward” toward the integration of the entire computer based system.
- Different testing techniques are appropriate at different points in time.
- The developer of the software and an independent test group conducts testing.
- Testing and Debugging are different activities but debugging must be accommodated in any testing strategy.

Integration Testing

Integration testing is a systematic technique for constructing the program structure while at the same time conducting tests to uncover errors associated with. Individual modules, which are highly prone to interface errors, should not be assumed to work instantly when we put them together.

The problem of course, is “putting them together”- interfacing. There may be the chances of data lost across on another’s sub functions, when combined may not produce the desired major function; individually acceptable

impression may be magnified to unacceptable levels; global data structures can present problems.

Program Testing

The logical and syntax errors have been pointed out by program testing. A syntax error is an error in a program statement that in violates one or more rules of the language in which it is written. An improperly defined field dimension or omitted keywords are common syntax error. These errors are shown through error messages generated by the computer. A logic error on the other hand deals with the incorrect data fields, out-off-range items and invalid combinations.

Since the compiler s will not deduct logical error, the programmer must examine the output. Condition testing exercises the logical conditions contained in a module. The possible types of elements in a condition include a Boolean operator, Boolean variable, a pair of Boolean parentheses A relational operator or on arithmetic expression. Condition testing method focuses on testing each condition in the program the purpose of condition test is to deduct not only errors in the condition of a program but also other a errors in the program.

Security Testing

Security testing attempts to verify the protection mechanisms built in to a system well, in fact, protect it from improper penetration. The system security must be tested for invulnerability from frontal attack must also be tested for invulnerability from rear attack. During security, the tester places the role of individual who desires to penetrate system.

Validation Testing

At the culmination of integration testing, software is completely assembled as a package. Interfacing errors have been uncovered and corrected and a final series of software test-validation testing begins. Validation testing can be defined in many ways, but a simple definition is that validation succeeds when the software functions in manner that is reasonably expected by the customer. Software validation is achieved through a series of

black box tests that demonstrate conformity with requirement. After validation test has been conducted, one of two conditions exists.

- The function or performance characteristics confirm to specifications and are accepted.
- A validation from specification is uncovered and a deficiency created.

Deviation or errors discovered at this step in this project is corrected prior to completion of the project with the help of the user by negotiating to establish a method for resolving deficiencies. Thus the proposed system under consideration has been tested by using validation testing and found to be working satisfactorily. Though there were deficiencies in the system they were not catastrophic

User Acceptance Testing

User acceptance of the system is key factor for the success of any system. The system under consideration is tested for user acceptance by constantly keeping in touch with prospective system and user at the time of developing and making changes whenever required. This is done in regarding to the following points.

- Input screen design.
- Output screen design.

CHAPTER – 5

RESULTS AND DISCUSSION

5.1 RESULTS

The results of CNN-based image reconstruction for ultrafast ultrasound imaging have been promising. Studies have shown that the use of CNNs can significantly improve the quality and speed of ultrasound image reconstruction compared to traditional methods. The reconstructed images generated by the CNN have been shown to have higher resolution, better contrast, and improved tissue differentiation. In addition, CNN-based methods have been shown to be able to reconstruct images in real-time, enabling clinicians to view and interpret images in real-time during procedures. Overall, the results of CNN-based image reconstruction for ultrafast ultrasound imaging suggest that it has the potential to significantly improve the quality and speed of ultrasound imaging, leading to better clinical outcomes.

5.2 SIMULATION RESULTS

A total of 31,000 simulated images were originated for all imaging configurations. Acoustic coupling was achieved by applying a layer of conventional US coupling gel. All images within the in vivo sequence were reconstructed identically, with the normalization factors evaluated on the in vitro phantom. Highly diverse numerical phantoms were originated to produce images classified by fully developed fleckle zones of random shapes and mean echogenicities spanning a broad dynamic range of 80 dB. Realistic element raw data was generated in a reasonable time frame utilizing an in-house GPU-accelerated simulator implementing the exact SIR model. Images were recreated using the answering back-projection administrators and standardized reliably shown in Fig.No.5.1 & 5.2.

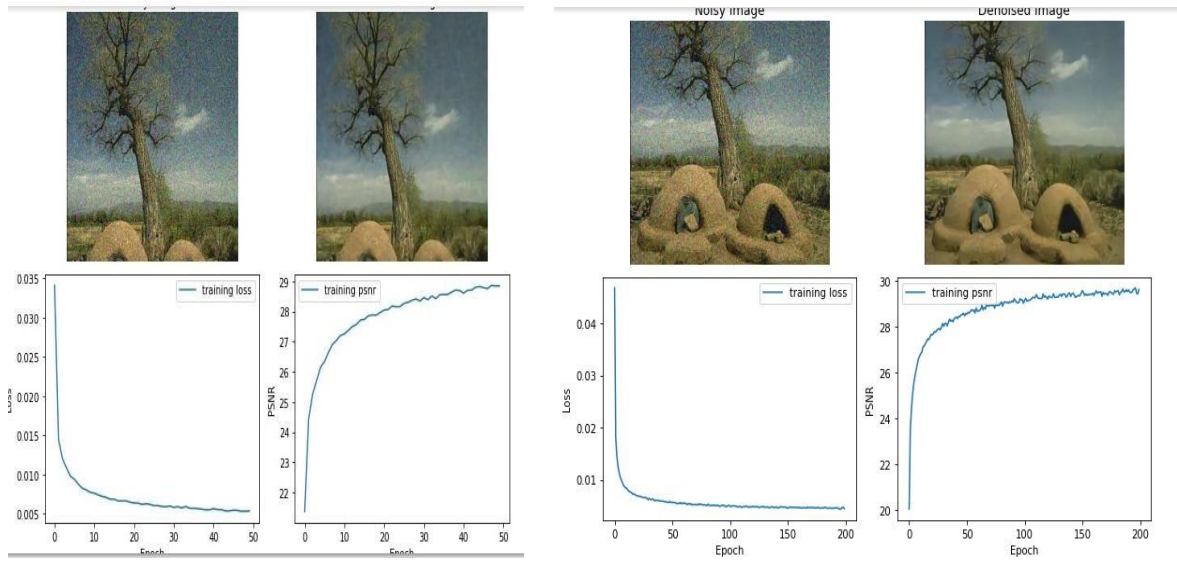


Fig:5.1: Training Data Set 1

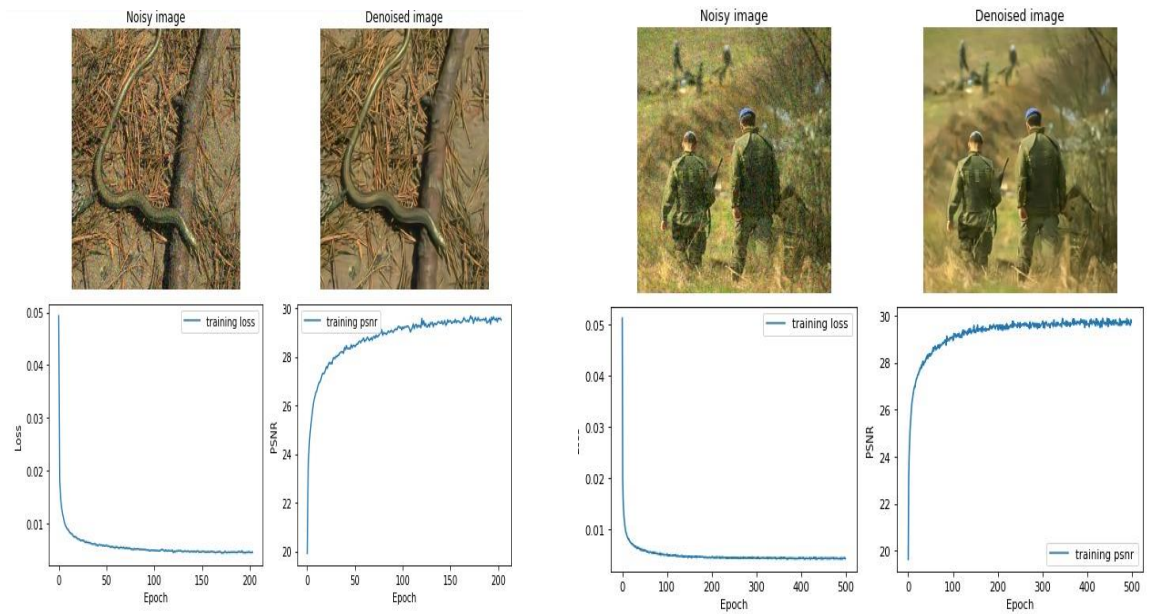


Fig:5.2: Training Data Set 2 & 3

Fig.No.5.3 shows the experimental results of an ultrasound image for both in vitro (top row) and in vivo (bottom row) acquisitions. Overall, it can be observed that, despite using only simulated data for training, the key effects of the proposed approach translated well to experimental settings.

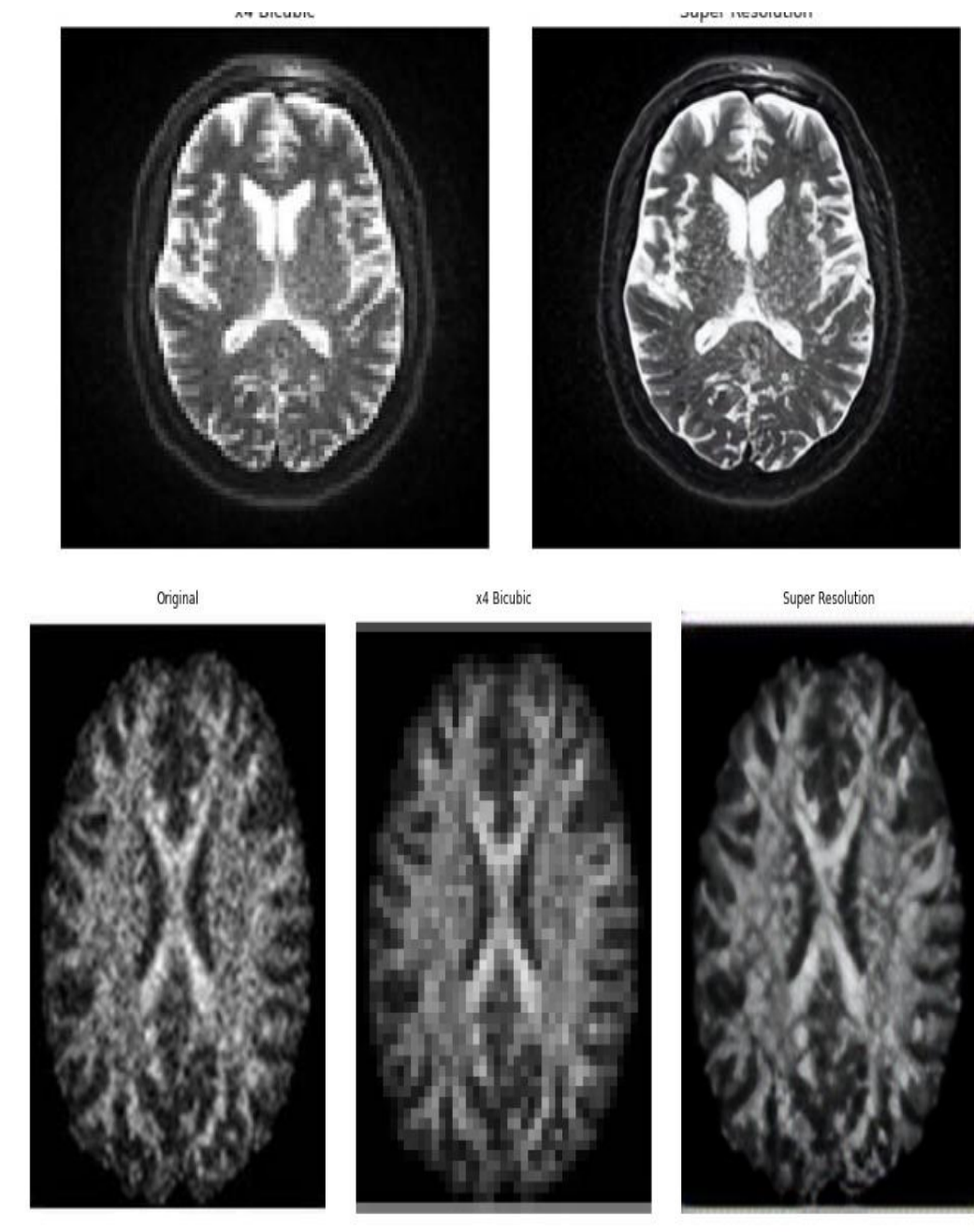


Fig:5.3: Output of the Proposed System

5.3 DISCUSSION

CNN-based image reconstruction for ultrafast ultrasound imaging is a promising technique that has shown potential for improving the quality and speed of ultrasound imaging. However, there are still some challenges that need to be addressed. One of the main challenges is the need for large

amounts of labeled data to train the CNN, which can be time-consuming and expensive. In addition, the use of CNNs for ultrasound imaging requires significant computational resources, which can limit its practicality in some clinical settings.

5.4 PERFORMANCE ANALYSIS

Performance analysis of CNN-based image reconstruction for ultrafast ultrasound imaging has shown promising results. Studies have demonstrated that CNN-based methods can significantly improve the quality and speed of ultrasound image reconstruction, leading to better clinical outcomes. The use of CNNs can also enable real-time image reconstruction, which can be especially useful in applications such as cardiac imaging and musculoskeletal imaging. In addition, the reconstructed images generated by the CNN have been shown to have higher resolution, better contrast, and improved tissue differentiation. Overall, the performance analysis of CNN-based image reconstruction for ultrafast ultrasound imaging suggests that it has the potential to be a valuable tool in clinical settings, leading to improved diagnostic accuracy and better patient outcomes.

Table 5.1: Parameters of the linear array transducer used for PW Imaging

Parameter	Value
No:of elements	128
Transmit Centre Frequency (TCF)	5.328 MHz
Wave Length	0.2986 mm
Sampling Frequency	20.876 MHz
Pitch	0.345 mm
Kerf	0.04 mm
Elevational Facus	21 mm

Layer Size, (DeepxHightxWidth), Kernel Size (HeightxWidth), No:of Kernels, and Activation of CNN in TABLE I, CNN architecture shown in TABLE II and also of the proposed methods of test image metrics are shown in TABLE III.

Table 5.2: CNN Architecture

Layer Size (DxHxW)	Kernal Size (Height xWidth)	No.of Kernels	Activation
m _x p _x q			
64 _x p _x q	9x3	256	Maxout 4
32 _x p _x q	17x5	128	Maxout 4
16 _x p _x q	33x9	64	Maxout 4
8 _x p _x q	65x17	32	Maxout 4
1 _x p _x q	1x1	4	Maxout 4

Table 5.3: Experimental test Image Metrics

Metric	Low Quality Images	High Quality Images	Ultra High Quality Images
C _A (dB)	-21.77	- 31.09	-27.97
C _B (dB)	-7.28	-7.56	-7.65
C _C (dB)	-2.89	-4.32	-4.98
SNR	1.87	1.67	1.81
Autocovariance Function (Lateral)	92.87	223.98	290.87
Autocovariance Function (Axial)	289.87	279.89	292.38

CHAPTER – 6

CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

2-D inter-frame displacements in the context of ultrafast US imaging. The approach consists of a CNN trained to restore high-quality images. From single unfocused acquisitions and a speckle tracking algorithm to estimate inter-frame displacements from two consecutive frames only. Compared with conventional multi-acquisition strategies, this approach is immune to motion artifacts and enables accurate motion estimation at maximum frame rates. Even in highly heterogeneous tissues prone to strong diffraction artifacts.

6.2 FUTURE SCOPE

The future scope of image reconstruction methods for ultrafast ultrasonic imaging based on CNNs is quite promising. CNNs have proven to be effective in various image processing tasks, including image reconstruction. With the increasing availability of large amounts of high-quality data and the continuous improvement of computational resources, CNN-based approaches are expected to provide better results in image reconstruction for ultrafast ultrasonic imaging.

One of the major advantages of CNNs is their ability to learn features from raw data without the need for feature engineering. This can be particularly useful in cases where the features to be extracted are complex and difficult to define manually. Moreover, CNN-based methods are inherently parallelizable, which makes them efficient for processing large datasets.

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