A DEEP LEARNING APPROACH FOR THE COMPLEX D-BAR ALGORITHM IN ELECTRICAL IMPEDANCE TOMOGRAPHY

Thesis to be submitted in fulfillment of the requirements for the degree of

M. Tech in Medical Imaging and Informatics

by

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CERTIFICATE

This is to certify that we have examined the thesis entitled **“A Deep Learning Approach for the Complex D-Bar Algorithm in Electrical Impedance Tomography”**, submitted by **Nemanth Kumar. M. S** (Roll Number: 21MM61R09) a postgraduate student of **Department of School of Medical Science and Technology** in partial fulfillment for the award of degree of **M.Tech in Medical Imaging and Informatics**. We hereby accord our approval of it as a study carried out and presented in a manner required for its acceptance in fulfillment for the Post Graduate Degree for which it has been submitted. The thesis has fulfilled all the requirements as per the regulations of the Institute and has reached the standard needed for submission.

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DECLARATION

I certify that

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1. ABSTRACT:

Electrical impedance tomography (EIT) is a non-invasive imaging technique that uses current measurements to produce images of the internal conductivity distribution of the body. The approach used for reconstructing EIT images is the complex D-Bar algorithm, which involves solving a highly non-linear inverse problem. However, this algorithm can be computationally expensive and difficult to implement. Though the D-Bar algorithm is robust and strong from noise, the reconstruction of the conductivity distribution is not so great for the data with the target and background conductivity. Recently, deep learning techniques have shown great potential in solving inverse problems in different imaging modalities. In this research, deep learning-based approach has been proposed to reconstruct EIT images, replacing the complex D-Bar algorithm. Specifically, a convolutional neural network has been developed (CNN) which is the modified U-Net on a large dataset of simulated EIT data to directly map the data obtained from the scattering transform to the conductivity distribution.

The proposed method has been evaluated on simulation data, and compare the results with those obtained using the complex D-Bar algorithm. We have also used evaluation Techniques known as GREIT figures of merit specifically used for testing the data used in Electrical Impedance Tomography. Our results show that the CNN-based method is superior to the complex D-Bar algorithm in terms of image quality and computational efficiency. The proposed method has the potential to significantly improve the clinical utility of EIT by reducing imaging time and providing more accurate and reliable images.

Key words: Electrical Impedance Tomography, Complex D- Bar Algorithm, Modified U-Net

2. INTRODUCTION:

Electrical Impedance Tomography (EIT) is a medical imaging technique that involves the measurement of electrical impedance of biological tissues to reconstruct internal images of the body. It is a non-invasive and low-cost technique that has potential applications in many clinical settings such as lung monitoring, breast imaging, and brain imaging.

The concept of EIT was first introduced in the early 1980s by Dr. David Holder, who used it to image the human chest. Since then, EIT has undergone significant development and has been used in numerous medical applications.

EIT operates by injecting a small current into the body and measuring the resulting voltage on the surface of the body. The distribution of the current and voltage can be modeled as a set of linear equations that describe the electrical properties of the body. The electrical properties of the body, including its conductivity and permittivity, are related to the physiological state of the tissue, such as the concentration of ions or the presence of fluid.

To generate an image, a set of electrodes is placed on the surface of the body, and a small electrical current is injected into the body through these electrodes. The resulting voltages are measured by the other electrodes on the surface. The voltage measurements are then used to solve a mathematical inverse problem, which involves computing the distribution of electrical properties within the body that best fits the measured voltages. The diagram for the electrical impedance tomography setup is given.

The conductivity is obtained by injecting the current in various types. The choice of the current pattern highly influences the resolution and quality of the image obtained through reconstruction. Different patterns are used for different applications. The different basic types of current injection patterns are adjacent pattern, opposite pattern and diagonal pattern. The current is injected in all the electrodes placed in the human body in pairwise fashion.[1]

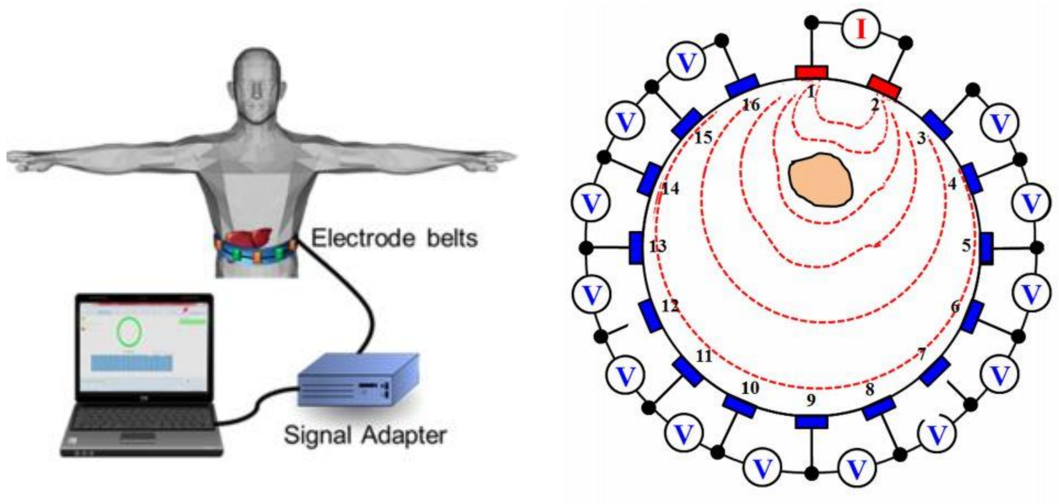

Figure 1. Electrode setup in Electrical Impedance Tomography

Electrical impedance tomography (EIT) has a wide variety of applications in the medical field and beyond. One of its most popular uses is in lung imaging, where it can monitor lung function in real time without the need for invasive procedures. EIT can image ventilation and pulmonary perfusion, as well as monitor treatment response in patients with respiratory diseases such as COPD and ARDS.

In breast imaging, EIT has shown great promise in detecting breast tumors. Non-invasive and radiation-free, it is an attractive alternative to mammography. EIT has also been used in brain imaging to monitor changes in brain activity, which could be useful in diagnosing and monitoring neurological disorders such as epilepsy and stroke.

EIT has been applied to image cardiac function and diagnose heart disease. It can detect gastric emptying and bowel movements, and diagnose bowel obstruction and other digestive disorders. In addition, EIT can monitor muscle function and diagnose neuromuscular diseases. In dental imaging, EIT can diagnose tooth decay and periodontal disease. Besides the medical sector, EIT has industrial and environmental applications, such as imaging underground pipelines and monitoring oil spills. With its versatility and non-invasive nature, EIT continues to have an ever-increasing range of applications in many fields.[2]

Electrical Impedance tomography offers several advantages over other imaging modalities. One of the most important advantages of EIT is that it is non-invasive, meaning it does not require injections or exposure to harmful radiation, making it a safe imaging modality for patients of all age, including pregnant women and children.

Another advantage of EIT is its portability. EIT devices are small and lightweight, making them easy to use in a variety of clinical and field environments. EITs can provide real-time visualization of physiological processes, allowing clinicians to monitor real-time changes and adjust treatment accordingly. This capability of the EIT is especially beneficial in critical care settings where rapid decision-making is essential.

Compared to other imaging modalities such as MRI and CT, EIT is relatively inexpensive, making it an affordable option for hospitals and clinics. In addition, EIT can be used to image a variety of tissues and organs, including the lungs, brain, heart, and gastrointestinal tract, making it a versatile imaging modality.

EIT can also be used for continuous monitoring of physiological processes. Clinicians can use EIT to track changes over time, which can help assess treatment effectiveness and make adjustments as needed. This is especially important in the management of conditions such as acute respiratory distress syndrome (ARDS) or during surgery.[3]

In summary, EIT has several advantages over other imaging modalities, including non-invasive, portable, real-time, inexpensive, secure, flexible, and suitable for continuous monitoring of physiological process. These advantages make EIT an excellent choice for many clinical settings, including critical care and surgery, where fast and accurate imaging is required.

The inverse problem in EIT involves reconstructing the distribution of electrical conductivity or impedance within the body from the measured electrical currents and voltages. This involves solving a complex mathematical problem, as there are many possible distributions of conductivity that could produce the same set of measurements. The goal of the inverse problem is to find the most likely distribution of electrical conductivity

3. LITERATURE REVIEW:

The paper "**A Rotational Invariant Neural Network for Electrical Impedance Tomography Imaging without Reference Voltage: RF-REIM-NET**" introduces a rotational invariant neural network to handle the ill-posed inverse issue of Electrical Impedance Tomography (EIT). The authors present a novel method for reconstructing EIT images that does not require a reference voltage, making EIT more feasible for usage in a variety of applications.

The suggested network, known as RF-REIM-NET, employs a unique architecture that includes a real and imaginary component of impedance measurements to build rotationally invariant feature maps. The authors tested the network's performance with synthetic and experimental EIT data, demonstrating that the RF-REIM-NET produces accurate and robust EIT picture reconstructions.

The paper **"The D-Bar Algorithm Fusing Electrical Impedance Tomography with A Priori Radar Data: A Hands-On Analysis"** looks into a technique for improving the spatial resolution of Electrical Impedance Tomography (EIT) by incorporating a priori information into the D-Bar algorithm's EIT reconstructions. The authors suggest a unique method for reconstructing images with higher resolution that integrates structural information. The new method was tested on numerical phantom tests, and the findings showed an improvement in spatial resolution over the standard D-Bar methodology.

The study's findings are relevant since EIT has showed tremendous promise in a variety of medical applications, but its spatial resolution is restricted due to noise. The suggested technology has the potential to transform EIT imaging and have a substantial influence on medical imaging. However, additional study is required to evaluate the proposed method's performance on experimental data and to investigate the proposed method's potential for clinical applications.

Finally, by suggesting a novel strategy for enhancing the spatial resolution of EIT images, the work makes an important contribution to the area of EIT imaging. The proposed technique has the potential to considerably improve EIT's use in a variety of medical applications.

The article **"Deep D-Bar: Real-Time Electrical Impedance Tomography Imaging With Deep Neural Networks"** describes a framework that uses convolutional neural networks (CNNs) for postprocessing of direct convolutional techniques. Reconstruction of problems in electrical impedance tomography (EIT). The authors emphasize that EIT is a non-horizontal problem that requires innovative techniques to produce accurate images. The article shows that the CNN approach provides a strong foundation for direct post-processing, resulting in a clean and reliable EIT structure. The findings of this article are significant because they suggest solving a major problem in generating clean images in EIT.

The publication **"The D-Bar method for electrical impedance tomography—demystified"** presents an overview of a family of computational inversion methods for the inverse issue of electrical impedance tomography (EIT). The purpose of this paper is to debunk the D-Bar approach for EIT and present an account of its evolution to the current state of the art. The D-Bar approach is a reconstruction technique that uses harmless electric currents to image the conductivity distribution inside the human body. In addition, the research shows how to apply convolutional neural networks for reliable and crisp reconstructions in EIT.

4. INVERSE PROBLEM FOR EIT:

The Electrical Impedance Tomography belongs to the class of inverse problems. The inverse problem in EIT involves reconstructing the distribution of electrical conductivity or impedance within the body from the measured electrical currents and voltages. This involves solving a complex mathematical problem, as there are many possible distributions of conductivity that could produce the same set of measurements. The goal of the inverse problem is to find the most likely distribution of electrical conductivity.

The first class of algorithms consists of various regularisation approaches. Their purpose is to minimise a two-part cost function. First, the vehicle of interest's physical behaviour is modelled. The algorithm assists in determining the best fit for the conductivity that can create these voltages given a set of voltage measurements. Second, the regularisation approach is used, which is critical in determining a legitimate solution. Total variation and Tikhonov regularisation are two common examples of variational regularisation algorithms..

The statistical inversion approach is the second type of procedure, in which picture reconstruction is modelled as a statistical inference issue. The measurement is represented as a random variable from which the posterior distribution is estimated. B.Markov chain Monte Carlo iteration, for example. This derivation can be used to calculate conductivity.

The final sort of image reconstruction is the direct method, which involves solving a system of linear equations that relate surface data to internal conductivity distributions. The Complex D-Bar Algorithm is a Direct form of inverse problem approach..[4]

The EIT technique is utilized to solve the issue of reconstructing the conductivities within a specific area, such as the human body, by analyzing the boundary voltage measurements. This involves positioning N electrodes uniformly along a section of the body, injecting a current pattern via these electrodes, and then measuring the resultant voltages. The EIT problem is given as:

$$\nabla(\sigma(z)\nabla u(z)) = 0, \; z \in \Omega \qquad (1)$$

where u → electrical potential, the 2D domain of interest (the slice through the body), the domain's location-dependent conductivity, and z is the position which is a complex number $z = x + j\,y$ (with $j = 1$).

A current is used to excite the system in equation (1). This is Neumann's boundary, which mathematically limits the partial differential equation of equation (1). This is written as:

$$\sigma(z)\frac{\partial u}{\partial \vec{n}}(z) = J(z), z \in \partial\Omega \qquad (2)$$

where $\vec{n}$ is the boundary's outward normal vector, J is the current density, and represents the boundary. Dirichlet boundary conditions can be mapped to Neumann boundary conditions. This map is called the "Dirichlet-to-Neumann map" (DN-map). It can be written as:

$$\Lambda_\sigma : u \rightarrow \sigma\frac{\partial u}{\partial \vec{n}} \qquad (3)$$

The D-Bar algorithm can be written in 4 steps:

1. Compute DtN map (Dirichlet to Neumann) Λ_σ from the voltage values.
2. Find the Scattering Transform within the |k| ≤ R1, Truncation Radius.
3. Solve the complex D-Bar equation
4. Recover the admittance values.

The equations governing the D-Bar algorithm can be found in the following papers.[5], [6]

The D-Bar algorithm is incapable of generating the output with the correct shape and size of the human tissues as the conductivity of the blood and other tissues are very close to each other. The computational complexity of the D-Bar equation solving is also very high since it uses the $O(z^*n \log n)^3$ which is not possible in generating data for a 3D model in the shorter span of time. Since, it is also a direct type inverse problem, generally this type of inverse problem is highly sensitive to noise. In order to generate the Image with correct conductivity of the human tissues and the shape of the human tissues, the deep learning technique as a replacement of the complex equations are capable of generating the high resolution of the image with equivalent conductivities of the human tissues and image without any distortions.

The steps involved in complex D-Bar algorithm are explained as follows:

1. **Finding the current and voltage values at the boundary:** The first step in finding the admittivity distribution in the human body is to inject current in the electrodes in the human body and to find the resultant voltages across the other electrodes.

2. **Dirichlet to Neumann Mapping:** The Dirichlet-to-Neumann (DtN) map is an important tool in EIT that relates voltage measurements at the boundary of a region to the internal conductivity of that region. The DtN map is used in the inverse EIT problem to obtain information about the internal conductivity distribution of an object from measurements made on its boundary.

   The DtN map is an edge operator that maps Dirichlet boundary data to Neumann boundary data. In the EIT, the Dirichlet boundary data represent the boundary voltage measurement, while the Neumann boundary data represent the current density across the boundary. The DtN map can be calculated using boundary integral equations involving the Dirichlet and Neumann boundary data with the internal conductivity distribution of the object. After the DtN map is computed, it can be used to solve the EIT inverse problem. The opposite problem is to find the internal conductivity distribution of the object from the boundary voltage measurements. The internal conductivity distribution is obtained by solving the DtN equation for the Neumann boundary data, and then using the Neumann boundary data to calculate the internal conductivity distribution using a Neumann-to Dirichlet (NtD) map as DtN mapping involves the partial differential equations. We find NtD map and find the inverse of it to find the DtN map.

   In general, the DtN map is an important part of the inverse EIT problem, as it allows the estimation of the internal conductivity distribution of an object from boundary voltage measurements.[7]

3. **Implementation of BIE:** Boundary integral equations (BIEs) are a numerical method used to solve boundary value problems for partial differential equations (PDEs) in a domain by reformulating them as integral equations on the boundary of that domain. Complex geometric optics (CGO) solutions refer to a method of constructing solutions

to certain partial differential equations (PDEs) using complex analysis and asymptotic analysis. Specifically, CGO solutions are constructed by finding complex-valued functions that satisfy the given PDE in the limit of large frequency or wave number.

4. **Scattering Transform:** The scattering transform is a nonlinear Fourier transform used in electrical impedance tomography (EIT) in the D-Bar method. It is designed for the EIT problem and is used to measured current/voltage data to compute a spatial prior in the k-plane from the forward problem.
   The scattering transform is critical in the D-Bar method's reconstruction procedure. It is used to compute the integral equation in the complex plane from the EIT data, which is then utilised to recover the target object's conductivity distribution. The scattering transform is also employed in difference imaging using the D-Bar method, which employs a modified scattering transform known as the differencing scattering transform to image the conductivity distribution within the D-Bar method.
   The scattering transform is a nonlinear transform that has been shown to have many advantages over other transforms in certain applications. One major advantage is its translation invariance, which allows it to capture spatially invariant patterns in a signal. The scattering transform has also been shown to have time-warping stability, meaning that it is robust to distortions in time, and to conserve energy, making it useful for signal processing in audio and other time series data.[7]

5. Compute the admittivity values from the scattering transform values: Then, the next step is to find the admittivity by first computing the matrix potential from the output of the scattering transform.

5. OBJECTIVE:

To overcome all the above disadvantages of the complex D-Bar algorithm, it is replaced by the Deep learning technique as it requires only a second or two for generating the image with its respective conductivity and susceptivity values. It also enables to obtain the conductivity distribution of the human body tissues in seconds without affected to noise artifacts. The objectives are:

1. To develop the CNN technique for obtaining the conductivity distribution from the values of the scattering transform.
2. To evaluate our technique and D-Bar algorithm with noisy data and to see the performance of the model.
3. To evaluate our model with the standard EIT evaluation techniques that is GREIT figures of Merit.

6. METHODOLOGY:

6.1. ABOUT THE DATASET:

Data is generated by using a simulation software called EIDORS which is specifically designed for the electrical impedance tomography. EIDORS is a software platform used for the reconstruction of images of internal conductivity distributions in objects or materials using electrical impedance data. It is an open-source MATLAB-based software package that allows to simulate and work with electrical impedance tomography data.

The value of conductivity and susceptivity used for generating the data is taken from the Italian national research council. The data is generated with the values of the conductivity taken from the above source mentioned and the susceptivity values are found from the following equation:

$$J = \sigma * \mathrm{E}$$
$$C = \epsilon 0 \epsilon r A/d$$
$$I = C\, dv/dt$$

J → current density, E → electric field, C → capacitance, ϵr → relative permittivity , ϵ0 → permittivity of the free space, ω → angular frequency and σ → conductivity.

The admittance can be written as Y= G + iB where i = $\sqrt{1}$ and the susceptivity B is obtained as:

$$G = \sigma \text{ , B} = \sigma \omega \epsilon r \epsilon 0 \tan \delta \qquad (4)$$

Where $\tan \delta$ → loss tangent, ϵr → $relative\ permittivity$, ϵ0 → permittivity of the free space, ω → angular frequency and σ → conductivity. So, the table containing the susceptivity and conductivity is given. [8]–[10]

Tissue Name	Conductance		Susceptance	
	50KHz	**500KHz**	**50KHz**	**500KHz**
Blood	0.700819624	0.748185833	0.491134	0.559763
Lung Inflated	0.102657178	0.123015106	0.01102	0.015132
Lung Deflated	0.261971558	0.306988398	0.068629	0.094236
Liver	0.072047232	0.148106351	0.00519	0.021935
Stomach	0.533711016	0.553980928	0.284836	0.306889
Heart	0.195433702	0.280730778	0.038194	0.078807
Pancreas	0.533962502	0.565819828	0.285109	0.320147
Bladder	0.21689266	0.227873027	0.04704	0.051925
Small Intestine	0.58029978	0.714761532	0.336736	0.510869
Uterus	0.525861229	0.54948675	0.276519	0.301926

Table 1. Conductance and susceptance values used in generating the data.

The data is generated with the ellipse object which is having the admittivity of the human body tissues mentioned above and the background is considered as the blood. The ideal image containing the ellipse which is called as target and the background is admittivity of the blood is drawn for the better understanding and it is as follows:

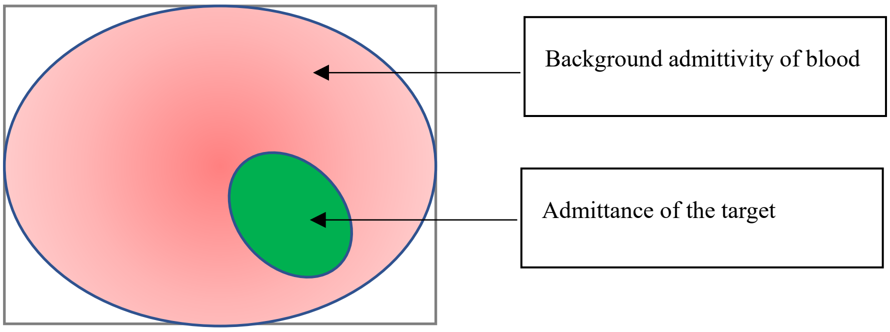

Figure 2. Ideal image output which is to be obtained from the electrical impedance tomography

The neural network is given with the scattering transform output and the image with its corresponding admittivity is obtained. So, the input is 2 matrix containing complex values. As the neural network is incapable of working with the complex values, the values are separated into two channels so as a whole the input consists of 4 channels as the input. The output is a single channel complex values, so the output splits to two channels as real and imaginary are separated.

The diagram of the model generated by EIDORS is given. It is a circular model similar to human body and the tissue is present in the human body which is having blood as the background. The problem in D-Bar algorithm is obtaining the image with proper shape deformation and so the deep learning is used to eliminate this problem. The diagrams are as follows:

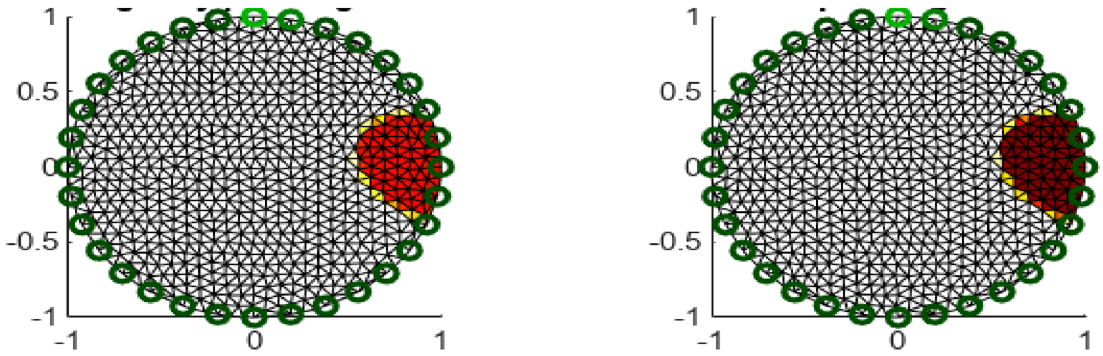

Figure 3. Generation of the model using MATLAB and EIDORS, left is the object having real values and the right is having imaginary values.

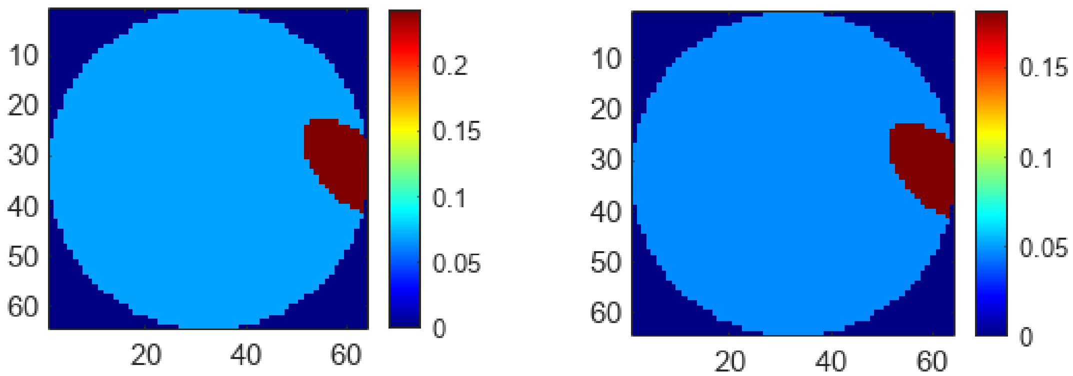

Figure 4. Expected Ideal admittivity images from the complex D-Bar algorithm, left is with real values and the right is with the imaginary values.

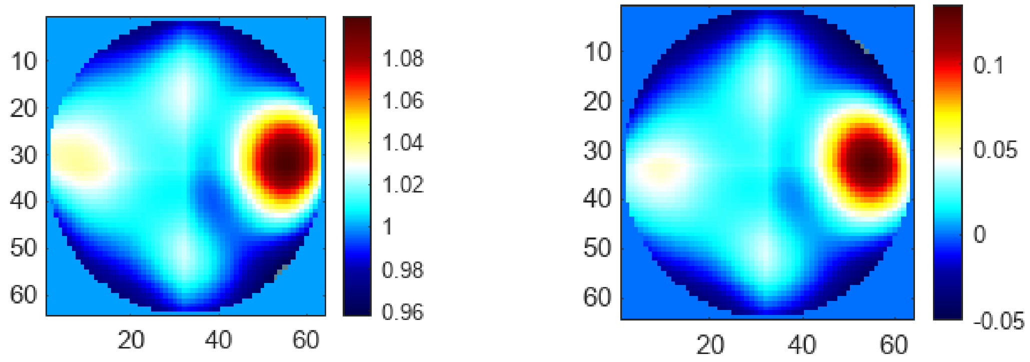

Figure 5. Expected Ideal admittivity images from the complex D-Bar algorithm, left is with real values and the right is with the imaginary values.

Modified Unet is a convolutional neural network architecture that has been used in the image reconstruction tasks, including medical imaging. It was originally designed for biomedical image segmentation but has since been applied to other tasks such as denoising, deblurring, and reconstruction. The architecture consists of skip connections, convolution 2d Transpose, concatenation layer, batch Normalization and the Dropout Layer. The parameters are also tuned in such a way that the model is capable of generating best image reconstruction.

6.2. DATA PREPROCESSING:

In deep learning, data standardization and normalization are two common techniques used for preprocessing data. While these terms are sometimes used interchangeably, they refer to different techniques with distinct purposes.

Data standardization rescales features to have a mean of 0 and a standard deviation of 1, creating a standard normal distribution. This technique is useful when there are differences in the scales of features, and it ensures that all features are on the same scale.

Data normalization, on the other hand, rescales features to a range between 0 and 1. This technique is useful when there are significant differences in the ranges of features, and it ensures that all features are on a similar scale.

Normalization aims to scale the values of a feature to a range between 0 and 1, making it easier for the model to learn the relative importance of different features. On the other hand, standardization transforms the features to have a mean of 0 and a standard deviation of 1, making it easier to compare the importance of different features based on their standard scores. In the context of deep learning, data normalization can help improve the convergence speed and stability of the training process by reducing the chances of gradient vanishing or exploding. It can also help prevent overfitting and improve the generalization performance of the model. In this specific application, normalization performed better in reconstructing the image than the data standardisation.

6.3. NEURAL NETWORK:

The diagram for the modified UNet is as follows. It consists of the following Layers.[11], [12]

1. Convolutional Layer: A convolutional layer is a fundamental component of a convolutional neural network (CNN), used for analyzing visual imagery and other types of data. It applies a convolution operation to the input, passing the result to the next layer. The purpose of a convolution is to convert all the pixels in its receptive field into a single value, which decreases the image size and brings all the information in the field together.

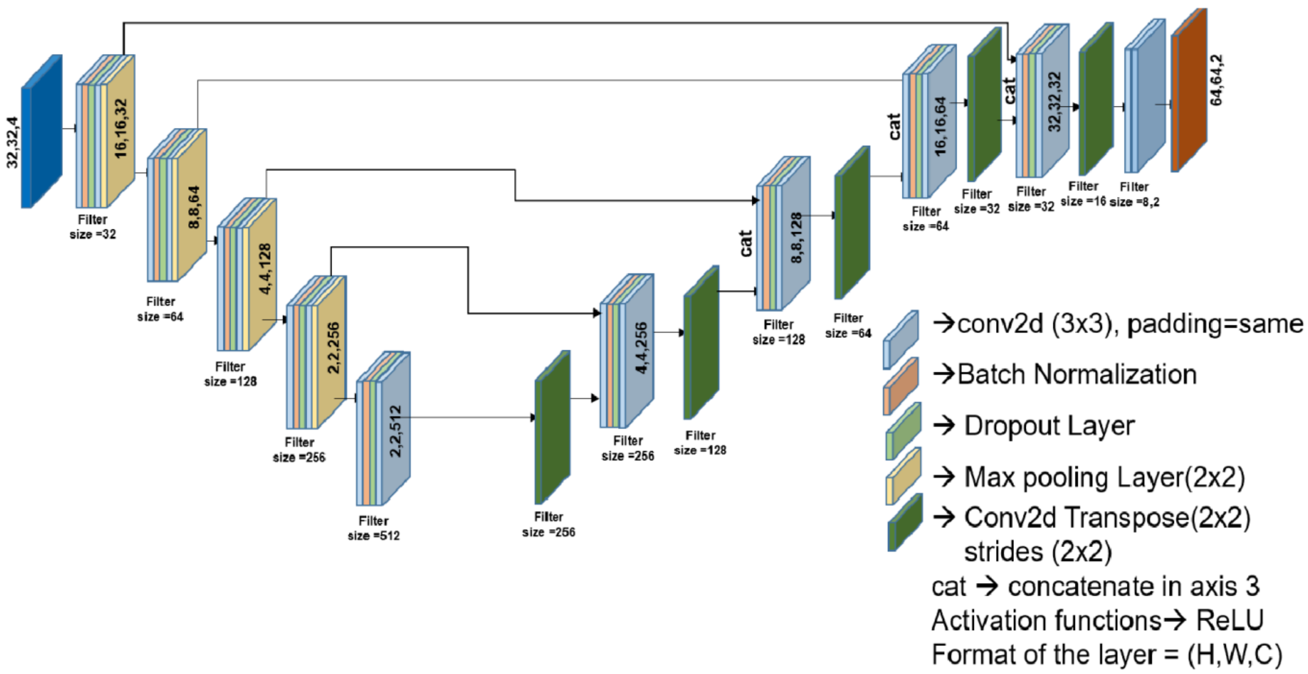

Figure 6. Modified UNet version used for the image reconstruction in EIT

2. Convolutional Transpose Layer: A Conv 2d Transpose layer, also known as a transposed convolution layer or deconvolution layer, is a type of layer in neural networks used to increase the spatial resolution of an input by performing a reverse convolution operation. The purpose of a transposed convolution generally arises from the desire to use a transformation going in the opposite direction of a normal convolution.
3. Skip connection: Skip connections are an important component of U-Net that help to improve the model's performance. The basic idea behind skip connections is to concatenate the output of an encoder layer with the input of a corresponding decoder layer at the same spatial resolution. This allows the model to preserve fine-grained details from earlier layers while also capturing high-level contextual information from later layers.

   Skip connections are particularly useful in U-Net because of its encoder-decoder architecture. The encoder is designed to extract features from the input image, while the decoder is designed to reconstruct the segmented image. Skip connections bridge the gap between the encoder and decoder by allowing the decoder to access the feature maps of the encoder at multiple scales.
4. Batch Normalization: Batch Normalization is a popular technique in deep learning used to normalize the inputs of a neural network layer to stabilize the learning process and improve model performance. It is a layer that applies a transformation that maintains the mean output close to 0 and the output standard deviation close to 1.

Deep learning, a subset of artificial intelligence, has a wide range of applications across various industries. Here are some examples of deep learning applications:

Computer Vision: Deep learning has revolutionized the field of computer vision by allowing machines to see and understand images and videos. Some examples include object recognition, facial recognition, image classification, and video analysis.

Natural Language Processing: Deep learning techniques such as recurrent neural networks (RNNs) and transformer models have greatly improved language translation, sentiment analysis, speech recognition, and text-to-speech conversion.

Autonomous Vehicles: Deep learning algorithms are used in self-driving cars to help them navigate roads and make decisions based on real-time data.

Healthcare: Deep learning is being used to develop predictive models that can assist in early detection of diseases, diagnosis, and treatment planning. Some examples include identifying cancer cells in medical images, predicting the risk of heart disease, and analyzing patient data to improve healthcare outcomes.

Financial Services: Deep learning algorithms are being used in the finance industry for fraud detection, risk management, and investment prediction.

Gaming: Deep learning has been used to develop intelligent agents that can play complex games such as chess and Go at a superhuman level.

Robotics: Deep learning is being used to develop robots that can learn from their environment and perform tasks autonomously.

Energy and Environment: Deep learning algorithms are being used to optimize energy consumption, reduce waste, and improve environmental sustainability.

Overall, deep learning has tremendous potential to transform various industries and improve our daily lives in numerous ways.

U-Net, a type of convolutional neural network (CNN), is commonly used in medical image reconstruction applications, particularly in segmentation tasks. Here are some advantages of using UNet in image reconstruction:

U-shaped Architecture: The UNet architecture is U-shaped, which means that it has a contracting path and an expanding path. This allows the network to capture both the high-level and low-level features of the image, resulting in more accurate segmentation and reconstruction.

Skip Connections: The UNet architecture uses skip connections between the contracting and expanding paths, allowing the network to preserve spatial information and reduce the loss of details during the encoding and decoding process.

Data Augmentation: UNet can be trained with a limited number of images due to its ability to generate augmented data by performing various transformations on the existing images. This helps to avoid overfitting and improve the accuracy of the reconstructed image.

Speed and Efficiency: UNet is faster and more efficient than traditional image reconstruction techniques, as it uses parallel processing to speed up the computation.

Transfer Learning: UNet can be easily fine-tuned for different medical image reconstruction tasks by using pre-trained models. This saves time and resources and allows the network to adapt to new tasks quickly.

Overall, UNet has proven to be an effective deep learning architecture for image reconstruction, particularly in the medical field, where accurate segmentation and reconstruction are crucial for diagnosis and treatment planning.

7. RESULTS:

The data obtained from the trained model is shown and it is exactly giving the output required with great shape and size of the target with high accuracy.

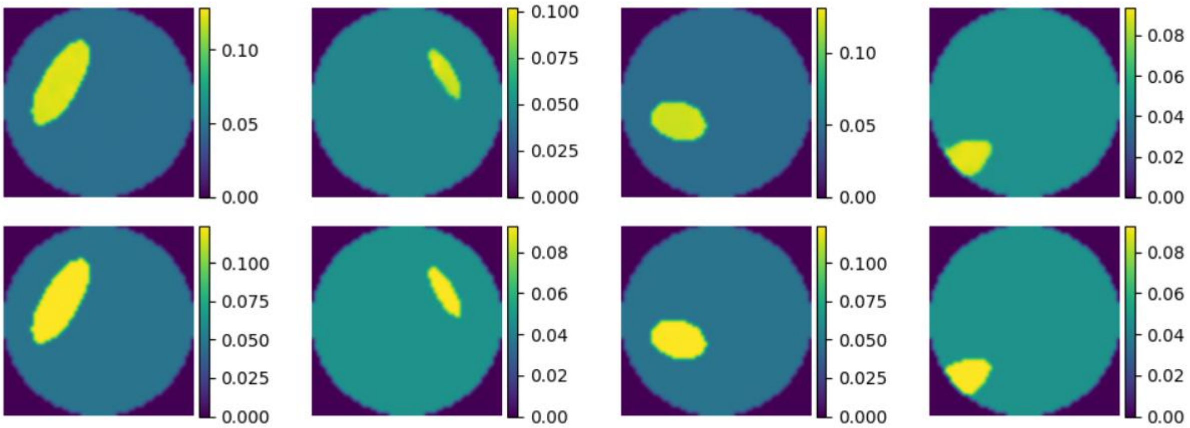

Figure 7. 1st row is the output obtained from the model and 2nd row is the ideal output of conductivity values respectively.

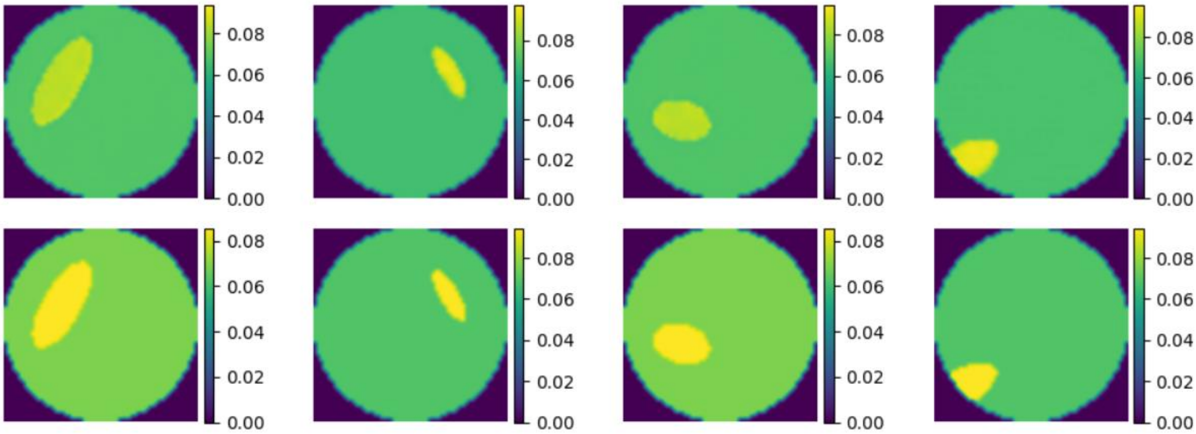

Figure 8. 1st row is the output obtained from the model and 2nd row is the ideal output of susceptivity values respectively.

To evaluate the technique performance, the GREIT Figures of merit is used where we used two parameters. One is Amplitude Response, the next one is Ringing Effect and some other common parameters such as SSIM and the PSNR is used.

Amplitude Response, Ringing Effect are the important parameters from the GREIT figures of merit which is the most important evaluation test for Electrical Impedance Tomography and it is used for finding the evaluation of the obtained results with the Electrical Impedance Tomography.

- Amplitude Response:- It is the parameter which shows that how the reconstruction of the object is present compared to the ideal object.

- Ringing:- It is a parameter which is inverted to the image and see how much the background is occupied.

The diagram for the Amplitude Response and the Ringing effect is as follows:

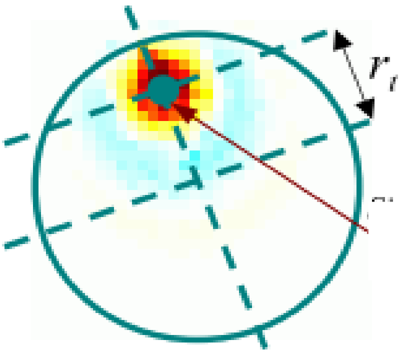

Figure 9. Diagram showing the amplitude response and Ringing effect.

The amplitude response and the Ringing is done by the following steps and it is done as per the context mentioned in the paper [13]

1. By finding the region of the target reconstructed by the complex D-Bar Algorithm and by the modified U-net version. This is compared with the ideal expected output.
2. To find the reconstructed region, the masking is done by finding the threshold value of 90% of its admittivity value and the background and target is separated.
3. The corresponding values which are required for the evaluation of EIT reconstruction, are now used for the evaluation.
4. Let us consider the pixel values which are inside the ellipse be considered as $\hat{x}$ and the pixels outside the ellipse are considered to be $\sim\hat{x}$.
5. The amplitude response is defined as the summation of the target region in the reconstruction image. AR = $\sum\hat{x}$. It should be ideally low.
6. The Ringing is defined as the standard deviation of the pixels outside the ellipse, i.e, background. R=std($\sim\hat{x}$). This should be low as well.

	D-BAR ALGORITHM	MODIFIED U-NET
Amplitude Response of the Conductivity	1.44	0.76
Amplitude Response of the Susceptivity	1.21	0.72
Ringing Effect of the Conductivity	1.02	0.98
Ringing Effect of the Susceptivity	1.012	0.97
SSIM of the Output	20.43%	99.45%

Table 2. Comparison of evaluation techniques of EIT

Noise analysis is also done by adding noise to the input and it is seen that the output generated by the neural network is way far better than that of the D-Bar algorithm. The diagrams for the different types of noise inclusions are shown.

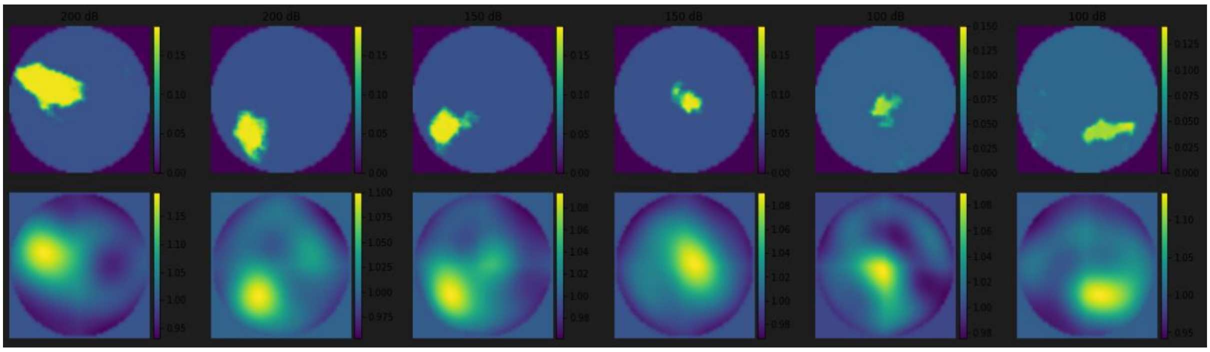

Figure 10. Conductivity Output of the network and the D-Bar algorithm with different noise additions to the input.

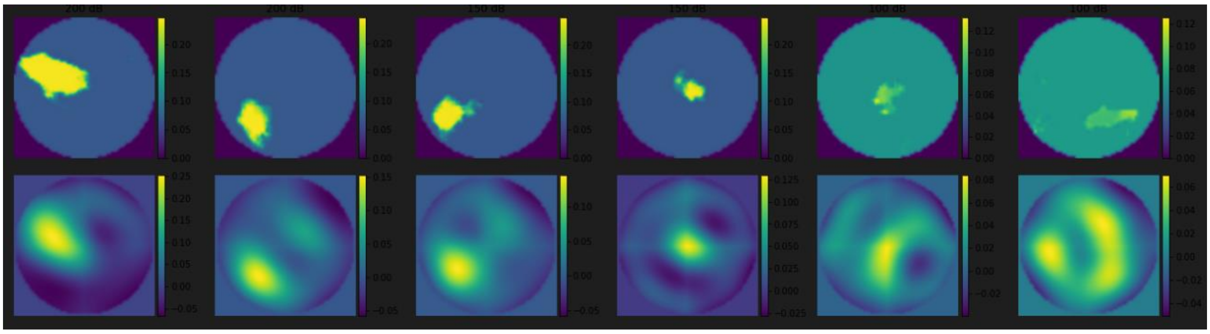

Figure 11. Susceptivity Output of the network and the D-Bar algorithm with different noise additions to the input.

The deep learning technique is better to noisy data compared to the complex D-Bar algorithm in generating the admittivity distribution output.

8. CONCLUSION:

Thus, the deep learning approach for the complex D-Bar Algorithm in Electrical Impedance Tomography is successfully implemented. The evaluation techniques also say that the deep learning technique is performing better than the complex D-Bar algorithm in regaining the original shape than the D-Bar algorithm.

9. FUTURE SCOPE:

The future scope of this work is that the complex valued neural network can be used to directly deal with the data which we have and this will be a great approach in solving the problems. This algorithm should also be implemented in real time and it is also capable of performing better than complex D-Bar algorithm as it is capable of generating the output in generating the output with good shape reconstruction and highly similar structurally.

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