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IMPACT OF ELECTROMAGNETIC WAVE INTERACTION WITH GEOLOGICAL LAYERS ON SUBSURFACE SENSING AND IMAGING

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Abstract
The role that electromagnetic (EM) waves play on geological layers is highly sensitive to the accuracy and speed of subsurface sensing and imaging technologies. This research aims to analyze geological factors such as soil texture, moisture level, stratification, and mineral content concerning EM wave propagation, attenuation, and reflection. Grounded in microwave remote sensing, electromagnetic induction, and ground penetrating radar (GPR) exploration methods, great care is taken towards exploration method. The research proves through analytical modeling and empirical field work that the dielectric constant and conductivity of the earth materials tremendously impacts the signal strength and its ability to penetrate into the ground. The presence of heterogeneous and anisotropic formations leads to scattering and signal distortion, which makes imaging harder to resolve. Having knowledge of these interactions helps to better interpret geophysical features, such as subsurface features, detecting the anomalies becomes easier, and enhances usage concerning monitoring the environment, evaluating archeological sites, estimating geological infrastructures, and hydrogeology research. The optimization of EM sensing techniques is advanced as they are ionized through the modulation of geophysical parameters to the geological conditions possessed, along with tailored configurations of sensors and geological settings.

Keywords: Electromagnetic waves, geological layers, subsurface imaging, ground-penetrating radar (GPR), electromagnetic induction (EMI), dielectric properties, signal attenuation, geophysical exploration, remote sensing, anomaly detection.

I.INTRODUCTION

The application of subsurface sensing and imaging technologies has increased in importance in fields such as geophysical exploration, environmental monitoring, archaeology, and infrastructure assessment.[5] These technologies depend upon the emission and reception of electromagnetic (EM) waves, which have interactions with layers of rocks below the surface of the Earth. The success and precision of such systems is highly sensitive to how EM waves propagate, reflect, and dissipate due to different materials found below the surface.[7] Antennas are important devices as far as interfacing the sensor device to the medium of geological material is concerned. Variation in design and function of antennas affects the gain, polarization, frequency, and radiation of EM waves, which determines its resolution and penetration depth.[9] Different geological layers having different dielectric constant, conductivity, and magnetic permeability give rise to alterations in propagation of the wave by reflecting, refracting, scattering, and absorbing it.[11]

As with other technologies, the region of space where EM propagates and the subsurface features allow for functionalities to be defined, the possibility of interoperability enhance. Driven by uncontrollable antenna parameters, like frequency band, EM wave polarization, and beamwidth, abstractions can achieve higher clarity and resolution signals. Signal distortion, loss, and noise are the primary challenges [4]. In addition, the obtained data is overly complicated on an interpretation level.\, For example, breadth barriers that are low enhance the clarity of the deepest section. However, mlx graph relies on antenna requiring higher frequencies to obtain finer details and reduced altitudes. As a progression, deeper holes allow a higher freedom of wrapping angles, but this mingles with vertical stacking without rotor blades.[13] Grasping how these interactions impact systems is critical towards enhancing specific antenna designs and optimally integrating subsurface sensing and imaging systems. [14]. This understanding allows for improved detection of subterranean irregularities, enhanced depiction of stratigraphic structures, and better-informed decisions for everything from mineral discovery to construction engineering.[15].

1.1 CHARACTERISTICS OF GEOLOGICAL LAYER

The description of geological strata is one of the first processes that helps in comprehending the interaction of geological strata with electromagnetic (EM) waves, such as with Ground Penetrating Radar (GPR) or other electromagnetic sensing technologies [2]. The dielectric permittivity and electrical conductivity, and magnetic permeability of the medium govern the capture mechanism of EM signals. Such characterization improves the level of precision achieved in realistic modeling and interpretation of the results of subsurface imaging.[16].

1.1.1 Dielectric Permittivity

Especially the relative permittivity (ε_r), dielectric permittivity (ε) relates to the extent a material can store electric energy in an electric field. It has a profound effect on the velocity and reflectivity of EM waves in geophysical media. Geological materials that have high moisture content, like wet clay or saturated soils, exhibit high permittivity. On the other hand, dry materials such as sands or granites tend to have low permittivity (ε_r ≈ 3–7). The difference in permittivity value between different layers creates conditions for partial wave reflection, which forms the basis for radargram interpretation in GPR.[17]. Characteristics such as mineral constituents, fluids saturation, and even granular size and porosity affect dielectric permittivity. Take, for instance, clay-rich soils which tend to have a delicate texture alongside high water retention, thus high permittivity. Permittivity measures can be obtained through lab tests (time domain reflectometry) or from field GPR observation data using inversion algorithms. This attribute is crucial in determining the EM wave velocity in the medium to be calculated which helps estimate depth using time-domain radar data.

1.1.2 Electrical conductivity

Electric conductivity (σ) gives insight into the broadband electromagnetic wave attenuation in a material. Clayeous sediments, saline soils, and even groundwater-saturated layers have high conductivity due to the abundance of saline waters, which results into significant energy loss through resistive heating (ohmic losses). This leads to shallow EM wave penetration and weak received signals, hence suboptimal subsurface imaging [23].

An electromagnetic wave's range determines the amount of Information obtained from the subsurface. With a high range of propagation speeds through Earth materials, moist clay easily surpasses dry sand or gravel, proving a massive elastic wave velocity with minimal damping. Practically, a soil box test in a lab can enable the direct measurement of conductivity, or alternatively deduced from borehole resistivity logs [24]. The epitome of highly conductive rocks and soils is accurate vertical conductivity characterization work on the signal reduction model for GPR frequency selection, where lower frequency waves penetrate deeper but yield finer detail, while higher frequency waves offer fine detail and get attenuated faster in conductive media[26].

1.1.3 Magnetic Permeability

Magnetic permeability (μ) refers to how a material will behave when placed in a magnetic field. The most common geological materials, like quartz, limestone, sand, and clay, are classified as non-magnetic substances, with a magnetic permeability (μ) almost equal to the free space (μ_0) values. However, in certain rock types and minerals, basalt rocks, magnetite, and iron-rich formations tend to have elevated magnetic permeability values, which affects the EM wave propagation, especially at lower frequencies. In high-frequency GPR systems, the lack of bandwidth is considered less dominant, but in cases involving electromagnetic induction, low-frequency geophysical surveys show significant improvement due to using unsaturated magnetic permeability [27]. For characterization purposes, magnetic susceptibility gauges at geological survey levels, magnetometers, and magnetron-derived multi-spectral systems can assist in measuring, while other methods are based on the degree of magnetic susceptibility measurements [28]. In several instances, considering magnetic permeability as an added parameter to the model works best under settings where ferromagnetic minerals are situated or where interpretive anomalies likely affected by field magnetic qualities are the goal.

1.2 RESEARCH OBJECTIVE

- To study the propagation characteristics of electromagnetic waves regarding their interaction with various geological layers with particular relations to reflection, refraction, scattering, and attenuation.
- Analyze the impact of geological attributes such as the dielectric constant, conductivity, moisture, ramification, and stratification on the propagation of electromagnetic waves in subsurface sensing.
- To scrutinize the effects of antenna design parameters such as frequency, polarization, and radiation pattern on electromagnetic wave transmission and reception for subsurface imaging.
- Refine and validate techniques to forecast electromagnetic wave action in complex, heterogeneous, and anisotropic geological formations to improve subsurface imaging precision.
- To evaluate the practical uses of the knowledge on electromagnetic wave interaction in geophysical exploration, environmental monitoring, and infrastructure evaluation.

II. LITERATURE REVIEW

Table 1: Comparison table for related work

Author(s) & Year	Main Areas	Findings	Methodology	Contribution to ANTENNA
Daniels, D. J. (2004)[1]	Ground-Penetrating Radar (GPR) theory and applications	Showed the impact on signal penetration and attenuation of EM waves as a function of the soil moisture content and soil conductivity.	Experimental & theoretical analysis	Emphasized the significance of the selection of frequency and antenna polarization
Jol, H. M. (2008)[20]	GPR for geological and environmental investigations	Elaborated the impact of heterogeneous subsurface structures on signal scattering and distortion	Field studies and simulations	Highlighted antenna beamwidth and frequency optimization for enhanced imaging
Annan, A. P. (1999)[3].	EM wave propagation in layered media	Developed models for reflection and transmission coefficients at interfaces of different dielectric materials.	Analytical modeling	Demonstrated the influence of geological stratification on antenna wave impedance matching
Chen, J. & Huang, X. (2015)[25].	Electromagnetic induction methods for subsurface sensing	Studied the impacts of conductive mineral layers on electromagnetic signal attenuation and phase change.	Numerical simulations	Proposed antenna tuning to frequency ranges less influenced by conductivity.
Guo, T. et al. (2019)[6]	Impact of anisotropy in geological formations on EM imaging	Found anisotropy leads to directional dependence of EM wave speed, affecting imaging accuracy	Laboratory experiments & modeling	Showed need for adjustable antenna polarization to reduce anisotropy effects.
Li, W. & Sun, Y. (2020)[18]	Antenna design for subsurface radar in complex geological environments	Created ultra-wideband antennas with enhanced performance for penetration and resolution in changing soil conditions.	Antenna design and field testing	Imaging clarity was improved through tuning the parameters of the antenna, demonstrating imaging advancement.

Wang, Z. et al. (2022)[8]	Subsurface imaging using multi-frequency EM waves	The multi-frequency technique enhanced the depth penetration capability while preserving superior resolution.	Experimental & signal processing	Highlighted multitasking band antennas for mitigating the balancing trade-offs between depth and resolution.
Zhang, L. & Xu, R. (2023)[10].	EM wave scattering in layered anisotropic media	Simulated scattering effects due to the existence of nonuniform boundaries and anisotropic layer interfaces	Computational modeling	Provided guidelines for antenna positioning and signal interpretation

The literature reviewed table 1 highlights the critical importance of geological layer properties concerning electromagnetic (EM) waves utilized in sensing and imaging applied beneath the Earth's surface. Multiple studies (Daniels, 2004; Annan, 1999; Chen & Huang, 2015) depict the importance of soil moisture, dielectric constant, and electrical conductivity regarding EM wave attenuation, reflection, and propagation. For example, a primary limitation on imaging depth and clarity is posed by high-conductivity materials like clay and saline soils that inflict rapid signal-loss. Further complications arise from the heterogeneity and anisotropy present within the geological formations. According to Jol (2008), Guo et al. (2019), and Zhang & Xu (2023), such irregularities cause scattering, distortion of waves, and velocity pertaining to directional dependence, thus limiting the accuracy of imaging unless catered for with advanced designs and signal processing systems. Geophysical antennas appear to be impactful concerning geological effects posed above and beyond imaging systems. That concern in mind, the work of Li & Sun (2020) and Wang et al. (2022) shows that specialized ultra-wideband (UWB), multi-frequency, and even multi-band operated antennas are capable of striking a desirable balance between peak imaging resolution and the depth of penetration. Operating parameters such as frequency, polarization, beamwidth, and other relevant angles must be adjusted to the targeted geological environment to achieve enhanced data quality. These findings have also highlighted the need for adaptive systems responding to changing subsurface conditions in real time. Moreover, the methods used across these studies, which include theoretical modeling, computational simulations, laboratory experiments, and field trials, are all encompassing and reinforce the conclusions while calling attention to the need for more unified approaches to address a wider applicability scope. It emerges from the synthesis of available research that optimizing performance with EM sensing requires more geomatic integration with the antenna system design, both considering the geological complexity. For improving imaging beneath the surface, advancements in adaptive antenna technologies, better modeling of EM-geological interactions, and novel data-driven interpretation techniques are important. Further developed research should focus on optimization using AI, real time calibration techniques, and inter-disciplinary frameworks to shift the balance of accuracy and reliability in subsurface exploration.

III. PROPOSED METHODOLOGY

3.1 Proposed Architecture

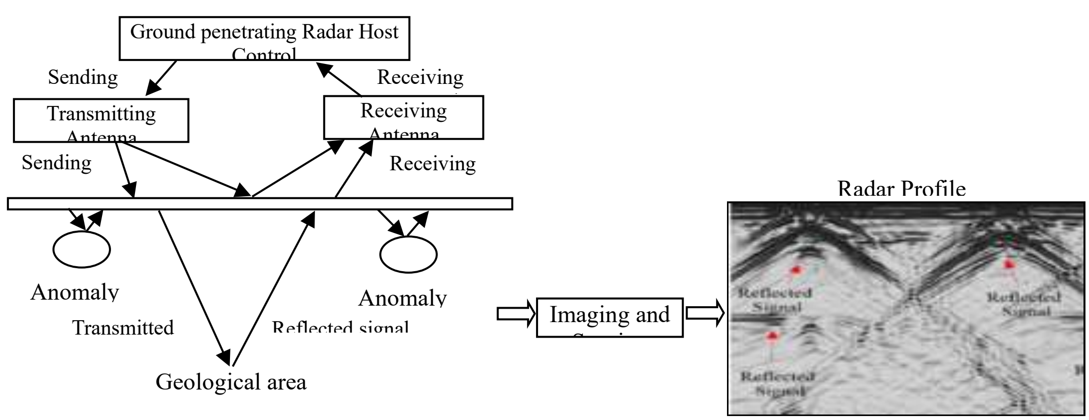

Fig:1 Proposed Architecture

The fig 1 demonstrates the operation of Ground Penetrating Radar (GPR) technology used for detecting objects and flaws below the surface. It has been divided into three distinct parts: system architecture (a), response to the GPR signal (b), and the radar profile output (c). In section (a), the GPR system comprises a control unit which is a host and the control unit involves the host connected to a transmitting and receiving antenna. The GPR system includes a host control unit, which is a system component that manages the transmission and reception of data signals. The radar signals are them internally captured through a ghost charge control unit that manages the them through a control unit. The transmitting antenna radiates electromagnetic pulses into the strata and geological layers. Strata and geological layers contain voice GPR radiance and reflections of certain offensive objects and mount base. When these signals hit an anomaly like an object that is buried or stuck in change material, gate control system reflection tend to bounce back from the surface edifice hold structure. These signals are attained by the receiving antenna. Mount and control unit gathers sustains in both case filling receives course receipt of angle control quad data package. Section (b) is concluded with rather simplified waveform sign capturing performed signals returning from anomalies that exist deep the subsurface surface. Changes in level, strength, and duration of signal pulses depend on the alteration of the bundles composed of geological materials that are located underground, and a few structures that exist. Actually, assumption shape the signal that serves for interpret scan data that is captured. Finally, section (c), is usually referred to as B-scan image radar profile. This image is obtained whenever a multiple fundamental components pulses are overline their segmentation on ground surface windows that are viewed from the above through shred at which is engaging. The radar profile's hyperbolic patterns suggest the existence of anomalies[19]. These patterns result from the reflection of radial waves off of concave or pointed surfaces beneath the ground. In section (a), the signals reflected and highlighted with red arrows indeed correspond to the anomalies identified. The diagram illustrates beautifully the working of GPR systems from sending signals and interacting with subsurface features to receiving and processing imagery which makes it useful in geology, archaeology, construction, and environmental science.[22].

3.2 Data Flow Diagram

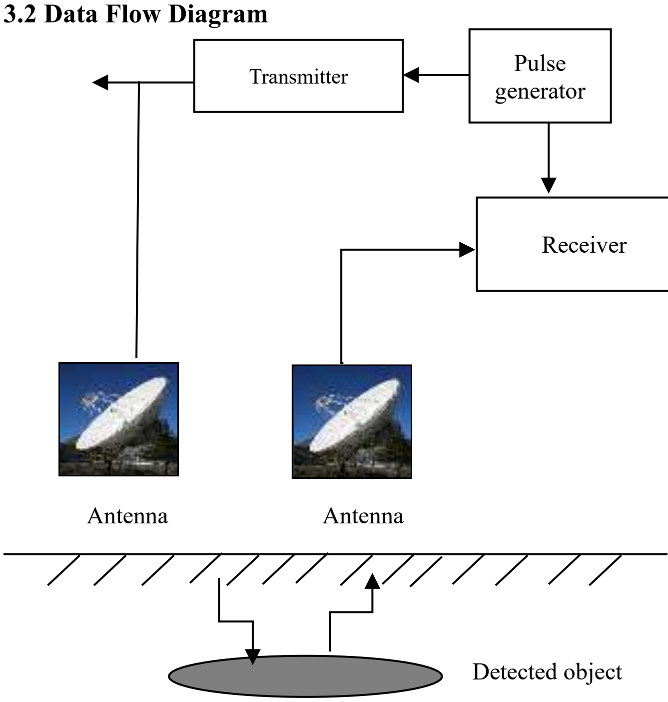

Fig:2 Data flow diagram for surface sensing and Imaging

Fig 2 summarizes the flow of Information in a Ground Penetrating Radar (GPR) system. It features the steps taken to identify objects below the surface. The process starts with the generation of electromagnetic high-frequency pulses in the system's initial component, the pulse generator. The transmitter processes the electromagnetic pulses and sends them to the corresponding antennas for further propagation. The antenna transfers the waves to the ground as GPR systems work with antenna. The waves are sent into the ground and will meet reflectors within it (like sub-surface structures or material interfaces). Part of their energy will bounce off back towards the surface. The signals received are still in data form and are processed by a receiver anterior to the collar. This unit generates and conditions data that is raw to be useful later. In this case the data has already been received so the process begins at the adapter which transforms the signal into essential Information like parameters of depth, shape and position of the object the was highlighted. To enable the user see the interpretation of the subsurface features, the system displays the Information through a visual unit display, which transforms the refined data temporally into an interpretable format. All in all, the diagram illustrates the steps along the GPR system, beginning with pulse generation and transmission, subsurface interaction, reflection, reception, analysis, and display, which would aid an operator to see objects that are buried underground.

IV. RESULTS AND DISCUSSION

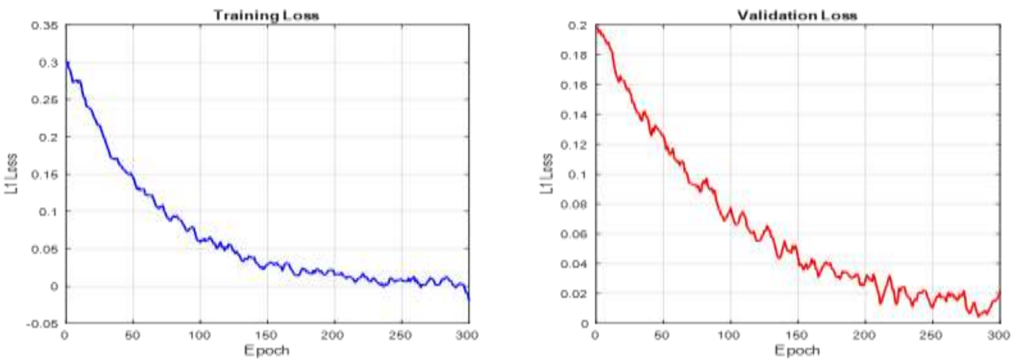

Fig: 3 Training and Validation loss for training process .

In the left image of Fig 3, and as we expected, we see that the training loss function of the UNet network decreases with increasing number of epochs. This implies, in this case, that the network is improving its performance and learning the features associated with GPR signals dealing with underground rock and stratigraphic structure information as the training progresses. At first, the training loss curve shows a steep drop; this often is the case when the network is said to be learning rapidly from the data. After some time, however, this rate of loss diminishes, and hence there is a plateauing effect where the rate of reduction is lower than the previous phase. This means that the network is likely at its upper limit of learning, thus hinting at converging behavior. The loss function is presented in the right image on the validation set. The same trend where a function decays with increasing number of epochs is also true on the validation set, which is a good sign that the model does generalize well to new data. The overall pattern of validation loss follows a similar trend as training loss, with no concerning upward shifts suggesting overfitting, which confirms strong generalization. To conclude, the two graphs of loss functions eloquently illustrate the UNet network's performance throughout the 300 epochs of training. For both training and validation losses, the trends remain consistently downward without overfitting. This highly strengthens the model's efficiency in forecasting underground rock formations and stratigraphic structures derived from GPR signals while showcasing their generalization prowess.

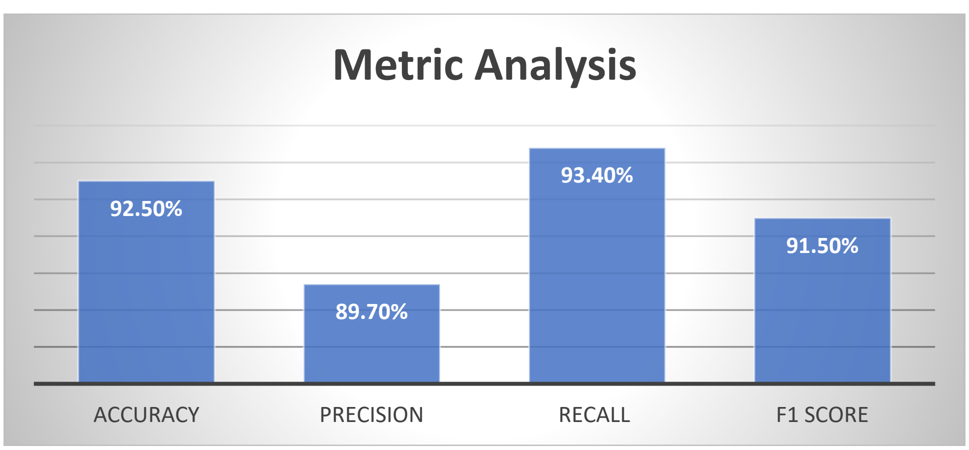

Fig: 4 Evaluation Metric Analysis

Based on the fig 4 metrics provided in the metric analysis chart, the model is evaluated and tracked through each stage of its construction using accuracy, precision, recall, and F1 score. Model accuracy has been assessed to be 92.5% which establishes that almost all predictions (positive or negative) made are correct. This is indicative of a very high level of trust in prediction results. Model precision is at the mark of 89.7, thus making almost 90% of all positive detections accurate. This denotes a very low percentage of misclassifications as positives. The model performs exceptionally well on recall, achieving a score of 93.4%. This value highlights the ability to identify positive cases correctly; therefore, a very high score in recall suggests that there are few positive cases missed. The balance in precision and recall gives an F1 score of 91.5%, a balanced figure signifying that neither of the two values was overly neglected. This adds to the reliability of the model as it is performing consistently without showing too much lean to precision or recall. To sum up, the model performs exceptionally on all fronts without leaning toward any feature while showcasing strong recall along with accuracy providing reliability for tasks when identification and minimizing missed cases is a necessity.

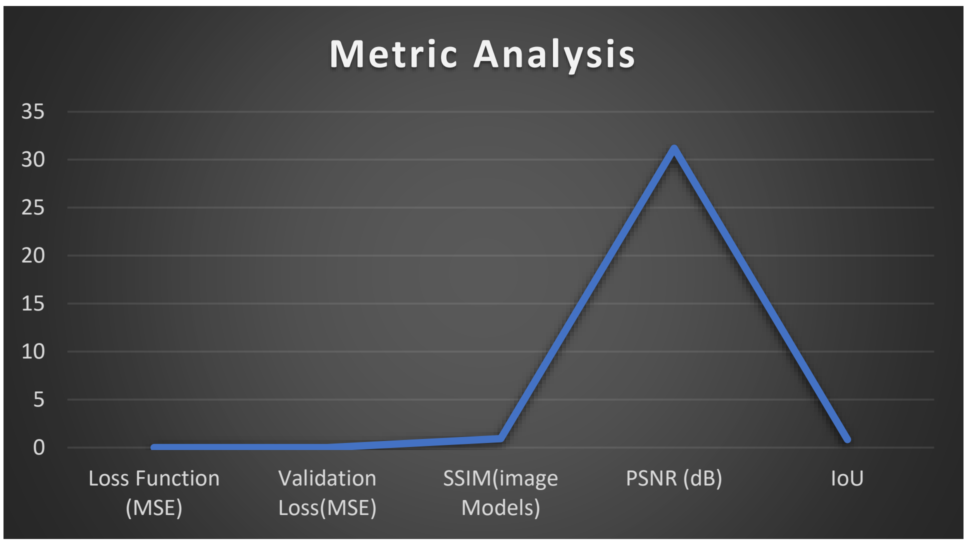

Fig:5 Metric Analysis for image-based performance

To interpret fig 5, the loss function and SSIM metric (as per the graph) both appear to have achieved moderately low values. This implies that while the model does well numerically, there is still plenty of room for improvement in perceptually relevant image quality. The line graph captioned 'Metric Analysis' demonstrates how an image-based model performs using five different metrics of evaluation: loss function (MSE), validation loss MSE, SSIM, PSNR(dB) ,and IoU. It can also be noted that both Loss Function (MSE) and Validation Loss (MSE) show very low values, meaning that the model fits the training data well and generalizes well to the validation set. The values also indicate that the model and the data set in question do not show a significantly high error divergence. Out of all the analyzed metrics, the most notable value is the Peak Signal to Noise Ratio (PSNR), which is much higher than every other metric PSNR depicts. This denotes that the images being reconstructed and produced by the model contain low amounts of noise when compared to the signal, showing proper image reconstruction or enhancement capabilities. Finally, PSNR appears to quite low exhibiting that the model is lacking when it comes to precision spatial estimation tasks like object segmentation and detection. The model shows great numerical accuracy with low loss and high PSNR values, displaying its effectiveness in image reconstruction or denoising tasks. However, the comparatively lower SSIM and IoU scores suggest moderate perceptual quality and low spatial fidelity, indicating some difficulty in meeting capture requirements, which could be improved for sensitive visual and spatial tasks.

V. CONCLUSION

The interaction of electromagnetic (EM) waves with geological layers critically considers the overall effectiveness and accuracy of subsurface sensing and imaging methods. Changes in geological composition, like moisture content, mineralogy, and stratification, create differences in EM waves' propagation, attenuation, and reflection. These interactions impact the depth of signal penetration, resolution, and data interpretation in GPR, EMI, and remote sensing applications. Knowing more about these interactions helps to optimize frequency selection, sensor geometry, design, and signal processing algorithms, which improves image and target detectability. Also, combining electromagnetic models with geological data enhances the reliability of imaging the subsurface in complex geological environments. Research of EM wave behavior in geological media is fundamental for developing geophysical exploration techniques, archaeological monitoring, environmental monitoring in civil infrastructure, and remote sensing.

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