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Fast Efficiency Googlenet using GPR Signal Processing

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Abstract: Ground Penetrating Radar (GPR) is a geophysical locating method that uses radio waves to capture images under the ground's surface in a least invasive way. Non-destructive testing relies heavily on the localisation and reconstruction of subsurface targets, as well as the calculation of object position and form utilising Ground Penetration Radar (GPR). In this design, the raw GPR data must be pre-processed. This data is then denoised using the DWT transform, and time- frequency data is processed with Fast efficient Googlenet. This approach applies the idea of global relative optimality from fast efficient deep learning to overcome the limitations of traditional algorithms that concentrate on extracting absolute features and therefore improving accuracy.
Keywords: Ground penetrating radar; non-destructive testing; Fast Efficient Googlenet; Discrete Wavelet Transform

I. INTRODUCTION

Metal pipe detection utilising earth Penetrating Radar (GPR) is a sophisticated technology for locating and mapping the location of metal pipes buried under the earth. GPR is a non- destructive geophysical technology that sends high-frequency radar waves through the soil and interacts with underlying structures. When these radar waves hit a metal pipe, they bounce back to the surface and are recorded by the GPR system. This reflection offers vital information regarding the pipe's position, depth, and, in certain cases, size. GPR is very useful for locating metal pipes because to their unique reflective qualities, which provide strong and recognisable signals. It has various benefits over conventional approaches like excavation and electromagnetic surveys, including the ability to cover huge areas fast, find pipelines without excavating, and produce comprehensive, real-time photographs of the subsurface. However, metal pipe identification with GPR may be difficult owing to variables such as pipe depth, surrounding soil conditions, and the existence of other objects that might interfere with the radar signal. Despite these problems, GPR remains an important instrument for correctly detecting metal pipes and guaranteeing the safe and efficient administration of subsurface utilities.

Ground penetrating radar (GPR) is a popular non-destructive device for detecting and locating underground pipelines [1]. Unlike prior detection approaches, GPR technology is non-destructive, needing no physical excavation and producing no ground damage. As a consequence, GPR is not only diverse and simple to use, but it is also very effective in detecting underground structures.

Furthermore, GPR has a high detection accuracy, enabling it to distinguish between subsurface objects and the medium while accurately identifying the target's location and shape. Because of its great effectiveness, GPR is widely used to detect shallow underground things in a range of sectors, including bridge deck detection, archaeology, and explosive detection. As a consequence, the use of GPR in subsurface pipeline identification is a promising field with practical applications[2]-[5].

Metal pipe identification is vital in many industries, including urban infrastructure management, construction, and utility maintenance. Metal pipes, which are commonly buried below, serve an important role in conveying water, gas, sewage, and other necessary services. Accurate identification and mapping of these pipes is required to avoid inadvertent damage during excavation or building operations, which may result in expensive repairs, service interruptions, and significant safety risks. Furthermore, metal pipes are susceptible to corrode over time, which may result in leaks or structural breakdowns. Early diagnosis of these vulnerabilities via effective inspection and monitoring is critical for maintaining infrastructure integrity and reducing public danger. Furthermore, metal pipe identification is critical when planning new projects or renovations, since knowing the location and condition of existing pipes allows for more efficient and safe project execution. As a result, accurate metal pipe identification is critical for ensuring infrastructure safety, lowering costs, and avoiding environmental damage.

Metal pipe identification using Ground Penetrating Radar (GPR) is difficult owing to various issues inherent in both the GPR technology and the properties of metal pipes. One important issue is that metal pipes often induce high reflections or scattering of radar waves, resulting in complicated and misleading signals in GPR data. This may make it difficult to discern between the pipe and other subsurface objects, particularly in noisy surroundings or when the pipes are buried at different depths.

In addition, the pipe's material composition, size, and direction might influence how radar waves interact with it, complicating data interpretation. In places with high soil moisture content or rusted pipelines, radar signals may attenuate fast, decreasing the efficiency of GPR. Furthermore, metal pipes often produce metallic "clutter" or misleading signals that might interfere with the identification of other subsurface structures, making exact detection and mapping of their position more challenging. As a consequence, complex processing methods and specialised equipment are often needed to solve these problems in metal pipe identification.

This research demonstrates applications for identifying and locating subterranean pipes. The apparatus is used to generate buried images in Ground Penetrating Radar. When collecting ground penetrating radar raw images, unwanted impurities such as noise and clutter are gathered. Raw photographs, often known as B-Scan images, have a sampling rate that exceeds 8 frames per second. However, manually evaluating a large number of GPR B-scan images takes time, and the results are highly dependent on the practitioner's expertise and prior knowledge. Large volumes of data were selected for pre-processing operations. The hyperbola reflected by the underlying pipeline indicates an underground radar image. The study's purpose is to provide an explanation for the hyperbolic pattern visible in Ground Penetrating Radar data, and the pipeline's location is determined using curve fitting and Dense Googlenet methods. The study presents a deep learning- based autonomous GPR technique for detecting and localising subsurface pipelines. First, a collection of 100 authentic GPR B-scans of pipelines is generated. Second, a dense GoogleNet model is trained to identify subsurface pipeline sections in GPR pictures.

II. LITERATURE SURVEY

However, the process of interpreting GPR data is a difficult one because of the complicated geometry of subterranean objects, changes in the amount of water present in the subsurface medium, and interference from other things that are located underneath. Due to the fact that it is often difficult to get appropriate findings by simply reviewing raw GPR pictures, it is standard practice to identify subsurface objects by identifying hyperbola in GPR B-scan images [11]. The evaluation of GPR data by the human eye, on the other hand, continues to be of great difficulty. It is possible that an expert will only be able to evaluate GPR data across a few kilometres of urban streets on a weekly basis, and the interpretations that they provide may not be reliable for a variety of reasons that are subjective. In order to assess GPR data and automatically extract hyperbolic feature information, researchers used a variety of signal transformation and processing methods. These approaches included the Hough transform [12]-[14] and Radon transforms [15].

Ground penetrating radar was proposed by M. Francisco and colleagues [2] as a non-destructive method for finding subsurface pipelines. This method was designed to minimise the effect on services in the intervention zone, such as leaks in subterranean utilities, which are especially prevalent in metropolitan areas. A learning-based strategy to detecting and visualising subsurface items was introduced by F. Jinglun and colleagues [3]. MigrationNet is an example of this approach. Through the use of ground penetrating radar, Q. Hoarau and colleagues [4] suggested a monostatic radar system that generates a Ricker wavelet for the purpose of identifying subsurface objects such as pipelines.A ground penetrating radar (GPR) detection method was suggested by W. Sun and colleagues [5]. This system makes use of a professional three-dimensional (3D) engine interface called OpenGL in order to provide an accurate three-dimensional visualisation of subsurface pipes. H. Yunpeng and colleagues [6] introduced an automated ground penetrating radar (GPR) technology that is based on a deep learning model and is used to locate and localise underground pipes. As part of its training, the YOLOv3 model has been instructed to identify subsurface pipeline locations. The automated detection of underground pipelines was suggested by B. Xu and colleagues [7], who made use of a deep learning system, three-dimensional ground penetrating radar (GPR) data, and an enhanced three-dimensional depth-wise separable convolution block. We present a data augmentation approach that is based on three-dimensional matrix rotation in order to increase the sample size of the dataset. This is then followed by a wavelet-based denoising method in order to get rid of direct wave interference. It was Y. Su and others (8). Using a key point regression mode, we proposed an end-to-end deep learning model for detecting subsurface utilities. This model would be used to identify utilities.

A successful clutter reduction neural network was developed by G. Yang and colleagues [9]. This neural network used a convolutional triplet attention module in the residual module in order to detect crucial areas that had certain scale attributes. Through the use of the network's adaptive mechanism, the outputs of several scale RSU modules were compiled in order to offer target replies that were both more precise and complete.In their paper [10], Q. Xu and colleagues suggested a technique that utilises deep learning to make predictions about the depth and radius of subterranean pipelines based on ground-penetrating radar data. GPR B-scan image preprocessing is used in order to arrive at an estimation of the depth and radius of joints.In order to develop non-destructive options for road subsurface health monitoring, L. Chenglong et al. [16] used ground penetrating radar (GPR), which is a real-time geophysical survey technology that employs electromagnetic radiation to investigate the subsurface.

It was discovered by L. Fanruo and colleagues [17] that smooth texture characteristics may be integrated with the many amplitude and phase spectrum parameters that are seen in deep cavity GPR signals. Using the time-frequency features of radar data, this study proposed an intelligent identification strategy for the deep road cavity based on a Multi-Channel and Dimensional Time-Frequency Convolution Neural Network (MCD-TF CNN). K. Toshinori et al. [18] proposed that the effects of pipe material, relative permittivity, and antenna frequency on depth estimation accuracy be quantitatively investigated using an artificial soil tank made of silica sand and predetermined physical characteristics. In addition to the GPR survey, relative permittivity measurements were taken using time-domain reflectometry (TDR) sensors set at different water levels. M. Nasri et al. [19] demonstrated hyperbolic recognition of various utility pipes using GPR images with variable penetration depths.

III. METHODOLOGY

Googlent is regarded as a superior instrument for ground penetrating radar (GPR) signal processing owing to its high computing capabilities, adaptability, and rapid data management. GPR signal processing demands high levels of accuracy, speed, and the capacity to handle massive datasets, all of which Googlent excels at because to its strong algorithms and machine learning integration. The platform is especially developed to increase subsurface imaging accuracy by reducing noise, enhancing signal, and extracting features. Furthermore, Googlent has an easy-to- use interface, making it suitable for both rookie and experienced GPR analysts. The tool’s scalability, support for various signal processing methods, and ability to visualize results in real- time further enhance its value in complex GPR data interpretation. This makes Googlent the best option for obtaining trustworthy and thorough insights from GPR data. The most novel advent of Fast efficient Googlenet in the field of computer vision in recent years has allowed for the development of a plethora of tools and frameworks to address a broad range of applications needing image interpretation and recognition. These applications involve a broad variety of functions, including picture recognition and interpretation. In addition, efforts have been made to process GPR images. Deep Convolutional Neural Networks were utilised to classify B-scan profiles as danger or non-threat. CNNs have outperformed other computer vision algorithms when using ground penetrating radar (GPR) data. This is particularly true for identifying landmines.It is possible that the basic feedforward neural networks described previously might be utilised as a starting point for applying neural networks to images. Connecting all of the nodes in one layer to all of the nodes in the layer below is a wasteful habit that should be avoided at all costs. To get considerably improved performance, connections must be pruned in a systematic manner using domain information such as image structure. This is important to get the intended effects. A deep convolutional neural network, or DDCNN, is a kind of artificial neural network designed to maintain a minimum number of connections across layers while keeping spatial correlations in the input. Following the initial organisation of the input into a CNN in the form of a grid structure, the input is propagated via layers that ensure the connections' integrity. During the transmission process, the actions of each layer affect a little amount of the layer that came before it. This is the case throughout the whole procedure. CNNs are an ideal option for applications that rely on images because of their capacity to generate extremely accurate representations of the data that is received. Backpropagation and gradient descent are two techniques used to train deep convolutional neural networks (DDCNN), which are similar to other types of artificial neural networks. These neural networks are composed of several convolutional and activation layers that are often alternated with pooling layers. Furthermore, in order to calculate the final outputs, CNNs often use fully linked layers in the process's latter stages. This is done to verify that the findings are correct.This design uses GPR B scans to capture pictures with a resolution of 512x512 pixels.

Rectified Linear Units, or ReLUs, are employed as activation functions in all convolutions performed using this technique.In convolutional layers, the actions of the previous layer are convolved using a sequence of tiny parameterised filters, generally 3x3, and then aggregated in a tensor $W(j,i)$, where j is the number of the filter and I is the number of the layer. This technique is done until numerous layers have transformed into convolutional layers. One approach for greatly decreasing the amount of weights that must be taught is to guarantee that all of the filters in the system have the same weights over the full input range. This approach is also known as translational equivariance across each layer. This weight-sharing strategy was inspired by the observation that qualities visible in one region of the image are likely to be seen in other sections as well. If you have a filter that can distinguish horizontal lines, for example, you may use it to identify them wherever they appear. This is feasible if you have such a filter.When all of the convolutional filters are applied to each input location of a convolutional layer, a tensor of feature maps is created. This tensor represents the feature mappings. The onlinear activation functions help to route the feature maps contained in a conventional layer. As a result, the whole neural network may approximate practically any online function. In certain cases, the activation functions are relatively basic rectangular linear units, often known as ReLUs. The representations of these ReLUs are indicated by the phrase $ReLU(z) = \max(0, z)$, and they may be changed in a variety of ways, including leaky and parametric ReLUs. When feature maps are fed into an activation function, new tensors, also known as feature maps, form on their own.

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Feature maps are another term for these data structures. Each feature map created by passing input through one or more convolutional layers is often combined with additional feature maps inside a pooling layer. This is done to get the intended outcomes. Pooling procedures provide a single integer representation of each place, although their input consists of relatively tiny grid sections. It is common practice to calculate the number using either the maximum (max-pooling) or the average function (average pooling). Both instances are shown below. The pooling layers allow the CNN to achieve a certain amount of translational invariance. This is because even little changes in the input picture might result in minute changes to the activation representations. Increasing the stride length is another option for achieving the downsampling effect afforded by pooling. When the pooling layers are eliminated from the network design, the architecture becomes simpler while maintaining the same level of performance.CNN's performance improved significantly as a direct result of a defined strategy. It is feasible that averaging a number of models in an ensemble produces better results than a single model. The dropout method is a strategy for ageing that uses random sampling of neural networks. The training method produces somewhat different networks for each batch of training data. This is because neurones are removed at random throughout the training process.

Furthermore, the weights of the trained network are changed in response to the optimisation of a variety of alternative network versions.The procedure of normalising in batches These layers are often added after activation layers, resulting in normalised activation maps. To compute these maps, remove the mean of each training batch from the total, then divide the result by the training batch's standard deviation. The inclusion of batch normalisation layers forces the network to periodically change its activations to zero mean and unit standard deviation as the training batch passes through these layers, acting as a regularizer for the network, speeding up training, and reducing its reliance on careful parameter initialisation.

A fully connected layer (FC) is introduced to the model to facilitate the adaptation of the classification task to a new domain. This is done to simplify the procedure. Specifically, we focus on the mechanisms involved for the development of the blocks: In addition to activation and dropout, the functions available for use include batch normalisation (BN) and activation. The batch normalisation function restricts the layer's output to a predetermined range. The layer's mean is 0 and its standard deviation is 1. By acting as a regularisation mechanism, this speeds up the training process while also increasing the stability of the neural network.The Dropout operation acts as a regulariser for each mini-batch that is being trained concurrently by blocking a small number of neurones. This is a simulation of the behaviour of a bagged ensemble made up of many neural networks. The dropout value is a mathematical representation of the proportion of inhibited neurones in a single layer, which may vary from 0 to100%.

Fig 1: Proposed Methodology

Denoised signal to be sent into the first layer as a vector is:

$X = [x_1, x_2, \ldots x_k]$ (1)

K stands for the amplitude of the signal. Afterwards, data normalisation is done to reduce execution load. The mapping of data points between 0 and 1 is known as normalisation:

$x = [\frac{-min}{max-min}]$ (2)

min and max are the lowest and highest values in the set of data, respectively. Before being sent into the convolution layer, this normalised data x is transformed into a 2D matrix using a reshaping procedure.

After covolution layer we got estimated the weight(w), bias (bj).

$x^{l}_{i} = \sigma[b_j + \sum_{a=1}^{m} w^{j}_{i+a-1} x^{l-1,j}]$ (3)

Activation function is indicated by the variable σ. Its nothing but ReLu,. ReLu function have higher efficiency and low execution time.

Max-Pooling Layer

By calculating the aggregation statistics of the nearby pixels, the Max-Pooling Layer maintains the scale invariant characteristic. They are useful for reducing dimensions in this way. There are two varieties of pooling: maximum and mean. The max-Pooling algorithm was used in our design. The max pooling layer avoids composite feature loss by finding the maximum response, or value, for each block. The max-pooling layer's final answer is:

$x^{l}_{i} = max^{r}_{n=1} \left(x^{l-1,j}_{(i-1)*T\ n}\right)$ (4)

where n is pooling size and T is pooling stride.

Following equation models the Hidden layer to output .Proposed method have this capability

$h_t = g(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$ (5)

$z_t = g(W_{hz}h_t + b_z)$ (6)

here, g indicates elementwise nonlinearity(it can be sigmoid or hyperbolic tangent), x_t is the input $h_t \in R^N$ is the hidden state having hidden units equals to N. Output is denoted by Z_t at instant t. pixel sequence $(x_1, x_2, \ldots, x_T)$ having T number of coefficient, then h1 (letting $h_0 = 0$),

$z_1, h_2, z_2, \ldots, h_t, z_T$.

Time Complexity of the Proposed architecture: The time complexity is calculated as:

$\left(\sum_{l=1}^{d} n_{l-1} \cdot s_1^2 \cdot n_1 \cdot m_1^2\right)$ (7)

above equation calculate the time complexity of the convolutional layer. Layer index is indicated by l which is d in number. Total filter number is η_1 in lth layer and their spatial size is denoted by s_1. Channel number of is η_{l-1} at lth layer. Output have spatial size of m_1 . Initial Convolutional layer required 7% of the execution time.

IV. EXPERIMENT & RESULTS

By comparing the Proposed Network to other well-known approaches, we can confirm that the proposed method is resilient. The same dataset with the same folds is used to construct and evaluate all of these strategies. Below is a summary of the outcomes that were attained.

True positive (TP):
Total correctly recognized samples of current class True negative (TN):
Total correctly recognized samples of remaining class False positive (FP):
Total incorrectly recognized samples of current class True negative (TN):
Total correctly recognized samples of remaining class

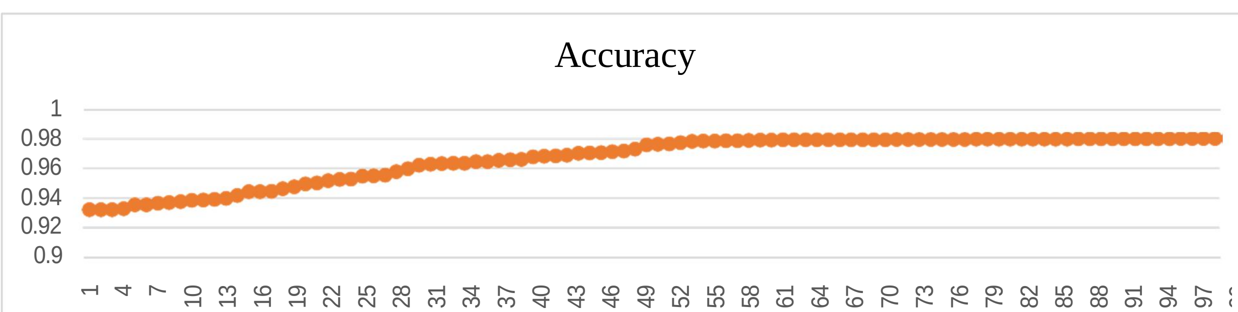

Fig 2 : Training Accuracy Vs epochs

Accuracy

$$Accuracy = [TP + TN] / [P + N]$$

Fall-out or false positive rate (FPR)

$$FPR = [FP] / [N]$$

Specificity , selectivity or true negative rate (TNR)

$$TNR = [TN] / [N]$$

Sensitivity, recall, hit rate, or true positive rate (TPR)

$$TPR = [TP] / [P]$$

While existing CNN and DNN reach 92% and 91% accuracy, respectively, the proposed network achieves 95.30%. The accuracy of other methods, such as LSTM and SVM, is 92% and 91%, respectively.

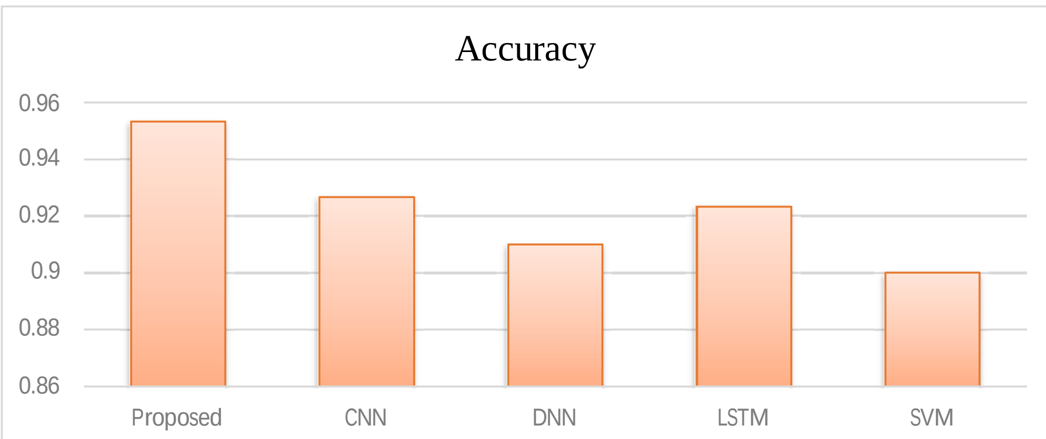

Fig 3 : Comparison of Accuracy

While existing CNNs and DNNs reach 98% and 97% sensitivity, respectively, the proposed network reaches 100%. Other methods, such LSTM and SVM, have sensitivity levels of 98% and 96%, respectively.

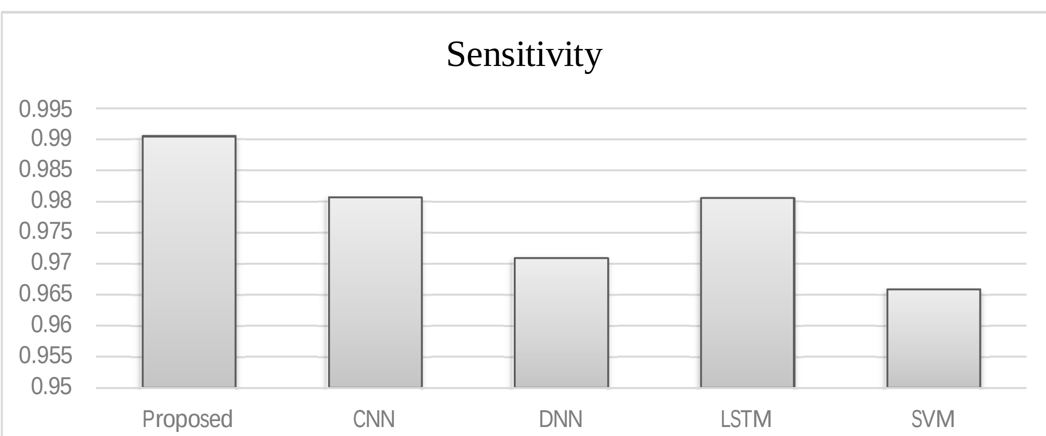

Fig 4: Comparison of Sensitivity

In comparison to previous CNNs and DNNs, the proposed network attains a Specificity of 97%. Specificity is 94% for LSTM and 91% for SVM, two alternative methods.

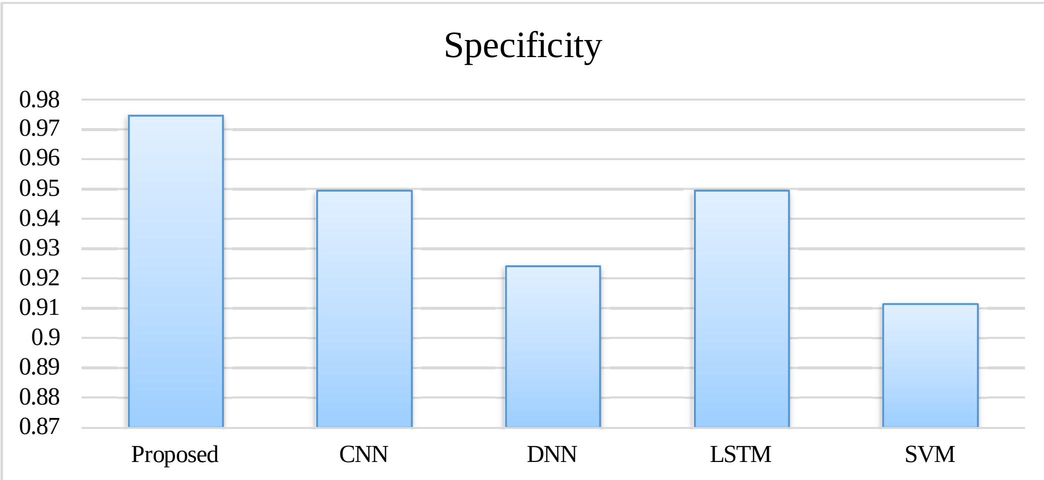

Fig 5: Comparison of Specificity

While competing CNNs and DNNs reach 91% and 90% specificity, the suggested network reaches 94%. Other methods, including SVM and LSTM, achieve a specificity of 89% and 91%, respectively.

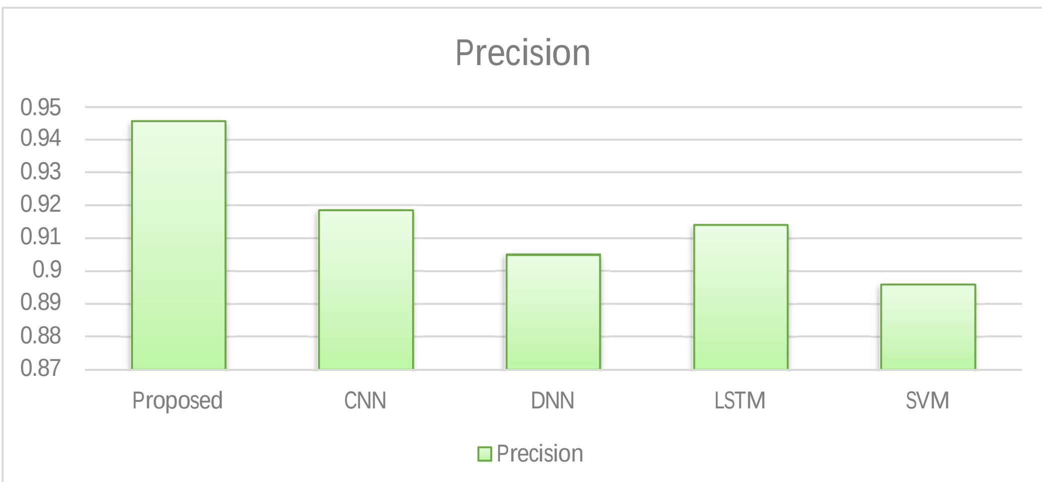

Fig 6 : Comparison of Precision

V. CONCLUSION

This study shows applications for detecting and localising subsurface pipelines. This study created a labor-saving way for boosting training data, mostly via the analysis of GPR findings using deep neural networks, and shown that the system can locate subsurface pipes with good accuracy when applied on real roads. Our suggested strategy offers various benefits over standard methods for boosting training data. First, it can create synthetic pictures that are comparable to genuine photos, considerably increasing the training dataset's variety and representativeness. Second, it can automatically annotate the created photos, saving time and reducing human error throughout the annotation process. Third, it may iteratively create new pictures from old ones, increasing the quantity and quality of the training dataset.

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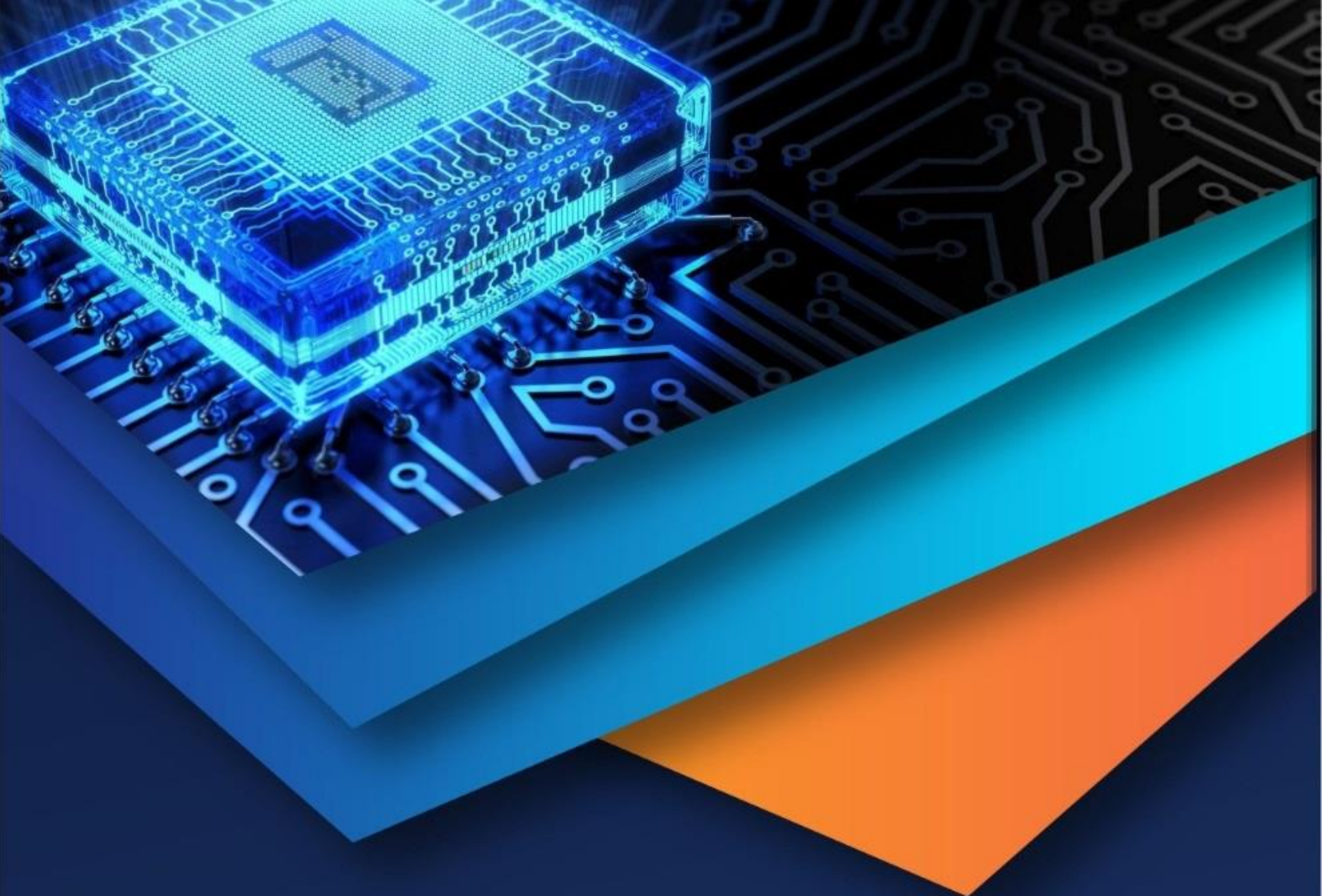

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