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RADAR IMAGING BASED ROAD SURFACE CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract:

A significant yet unfinished job is the creation of a surface recognition system for automobiles. The purpose of this research is to show how useful millimeter wave radar can be for surface discrimination in automotive sensing by analyzing images of actual road surfaces captured with a 79 GHz imaging radar and applying a novel approach to surface classification. The proposed experimental method utilizes a convolutional neural network to accurately categorize surfaces. Convolutional neural networks (CNNs) are a kind of Deep Learning method that can take an input image, give significance (learnable weights and biases), and then detect various characteristics and objects within that image. The convolutional neural network that autonomously learns unique characteristics for each class.

Keywords: Millimeter wave radar, radar remote sensing, radar imaging, electromagnetic scattering, convolutional neural network.

I INTRODUCTION:

For reducing the road accidents and to model the autonomous vehicle we have to know the road condition and type of road. To determine the kind of road, we categorize it using radar imagery and convolutional neural networks (CNN). The primary objective of this research is to classify roads and sidewalks using radar images (obtained from our mentioned paper). How the images are taken and

For what they are used. The development of autonomous vehicle (AV) technology has seen some success in recent years. Companies of all sizes are looking at AV as a potential way to cut down on traffic fatalities. Human mistake was shown to be the leading cause of traffic accidents in a European research. This causes over 25,000 fatalities each year on Europe's roads, or 49 deaths every minute. The monetary expenses are substantial even in the event of accidents with no casualties. These examples highlight the significance of AV due to its ability to eliminate human error and boost driver and passenger protection on the road. While advancements in AV technology have been rapid in recent years, there are still challenges to be overcome, including the creation of a reliable surface identification (Surface ID) system.

This system ought to remotely classify the road surfaces and warn the driver or AV computer of potentially hazardous road surfaces, ice, stagnant water, or changes in the road path, allowing the vehicle to remain securely under control as it transitions from one surface to the next and preventing serious accidents, injuries, and deaths. One of the most important features of autonomous driving is the ability to automatically adjust vehicle speed based on road conditions. With the Surface ID technology, drivers of four-wheel-drive cars will be able to switch between two- and four-wheel drive as needed, cutting fuel consumption and emissions. Radar, sonar, and light detection and ranging (LIDAR) cameras are only some of the sensor technologies that may be used to categorize road surfaces. The extreme resolution of laser-based LIDAR means that even minute details may be seen.

1.1 Radar:

In order to detect, localize, track, and identify objects of different types at great distances, scientists developed radar, an electromagnetic sensor. It works by sending out electromagnetic pulses in the direction of targets and then listening for the echoes that bounce back off of those things. The objects of the attack might be anything from birds and insects to the moon and stars. Radar may occasionally determine the form and size of such objects in addition to establishing their existence, position, and velocity. Radar can identify distant objects in poor weather and accurately measure their range, making it stand out from optical and infrared sensing technologies.

Because it uses its own light source (a transmitter) to detect its targets, radar is considered a "active" sensing instrument. It generally works at microwave frequencies, which span from about 400 MHz to 40 GHz (cycles per second) in the electromagnetic spectrum. Long-range applications have made use of the HF (high-frequency) or shortwave band (a few megahertz) as well as optical and infrared (lidar) frequencies. Radar systems differ in size from handheld devices to ones that would take up a whole football pitch, with the circuit components and other hardware adapting to the frequency being utilized.

1.2 Radar Imaging:

An echo measuring system is one way to characterize a radar imaging system. The antenna for the radar sends out millions of pulses of microwave radiation and analyses the characteristics of the echoes that return to it. The radar estimates the distance to the reflecting object by measuring the return wave's amplitude, phase, and arrival time. In other words, the radar can tell if the wave is returning at its peak, trough, or anywhere in between. Images and other valuable goods may be derived from the combination of these ranges, amplitude, and phase data. The main benefit of radar imaging is its ability to see through cloud cover. Microwave radiation, which radars produce in bursts, has far longer wavelengths than visible light and is thus unaffected by atmospheric conditions like cloud cover, dust, and gas. Only radar, among remote sensing methods, can reliably gather data in inclement weather.

II EXISTING METHOD:

Multilayer perceptron (MLP), a kind of feed forward artificial neural network (ANN), was the most accurate statistical classification method for surface identification. An advanced multilayer feed-forward neural network may learn by using the back propagation technique. It develops a collection of weights that may be used to predict the class label of a tuple over repeated iterations. An input layer, a hidden layer, and an output layer make up a multilayer feed-forward neural network. Similar to the delta rule, the back propagation method uses gradient descent to attempt to minimize the sum of squared deviations between the intended and actual network outputs. The study typically assumes a sigmoid activation function, which is semi linear (differentiable and monotonic). There are two phases to the algorithm:

- feed forward phase
- feedback phase

Multilayer perceptrons (MLPs) are a type of fully connected feed forward ANN. See Terminology for a full discussion of what we mean when we say "artificial neural network" (ANN) and specifically "multiple-layer perceptron" (MLP) network. "Vanilla" neural networks are occasionally used to refer to multilayer perceptrons with a single hidden layer.

The nodes are arranged into at least three layers in a multilayer perceptron (MLP): input, hidden, and output. Except for the input nodes, every other node in the network stands in for a neuron whose activation function is nonlinear. Back propagation, a supervised learning approach, is used in MLP's training process. The MLP differs from the linear perceptron because to its multi-layered structure and non-linear activation. It is able to differentiate between data that cannot be split linearly.

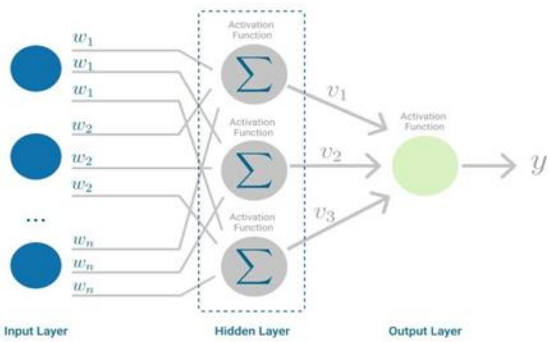

Fig 1. Multilayer Perceptron

Disadvantages:

There is more than one local minimum for a non- convex loss function in an MLP with hidden layers.

The performance of an MLP can be improved by adjusting certain key parameters, such as the number of hidden neurons, layers, and iterations.

The feature scaling of MLP is very sensitive

III PROPOSED METHOD:

3.1 CNN:

In the area of machine learning, artificial neural networks excel. Categorization of images, sounds, and texts is only one of the numerous applications for artificial neural networks. Images are classified using convolutional neural networks, while word sequences are predicted using recurrent neural networks, particularly an LSTM. In this part, CNN's pillars will be created. More than one convolutional layer may be included in a convolutional neural network. The amount and complexity of the data determine the ideal number of convolutional layers.

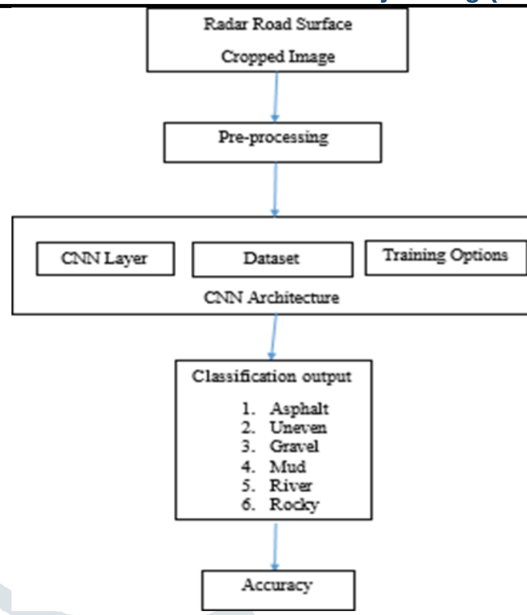

Fig 2. Block Diagram of Proposed Method

3.2 CNN Architecture:

An input layer, several hidden layers, and an output layer make up a convolutional neural network. Because the final convolution and the activation function serve as a mask between the inputs and outputs of the preceding layers in a feed-forward neural network, we contend that the intermediate layers are "hidden" in the network. The convolutional operations in a convolutional neural network happen in the hidden layers. This often involves a layer using the dot product of the convolution kernel as its input matrix. Commonly used is the Frobenius inner product with the ReLU activation function. The convolution approach creates a feature map that is provided into the input of the next layer by sliding the convolution kernel along the input matrix for the layer. The normalization, fully connected, and pooling steps come after.

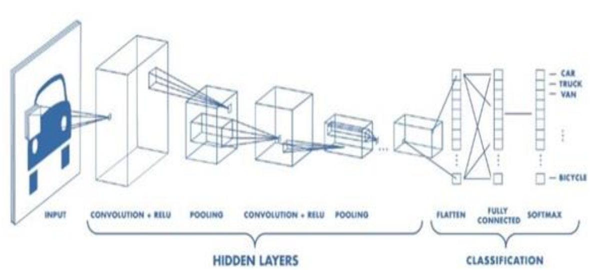

Fig 3. Architecture of a CNN

3.3 Advantages:

When compared to its predecessors, CNN's key benefit is that it can recognize essential properties automatically, without human involvement.

The computational overhead of CNN is minimal. It performs parameter sharing and employs specialized convolution and pooling algorithms. This makes it possible for CNN models to function on any platform, increasing their appeal.

3.4 Applications:

Analyzing images

The Translation and Processing of Languages

Detection of Paths

Speech recognition

Forecasting

IV: RESULT AND DISCUSSION:

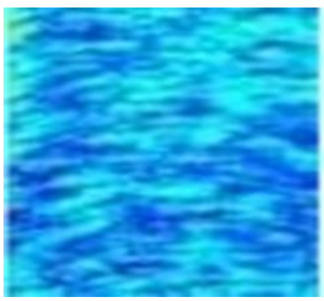

Fig 4.1 Original Image of RADAR

```
Training on single CPU.
Initializing input data normalization.
|==========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|==========================================================================================================|
|       1 |           1 |       00:00:00 |       11.11% |       33.33% |       2.3277 |       2.7334 |          0.0100 |
|      30 |          30 |       00:00:02 |      100.00% |      100.00% |   2.7154e-06 |   2.8573e-05 |          0.0100 |
|==========================================================================================================|
Output of CNN Classifier is: ASPHALT
Final Validation Accuracy:
   83.3333
```

Fig 4.1.1 After Testing the original Image by using CNN was Asphalt and its Accuracy

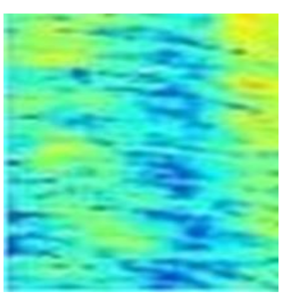

Fig 4.2 Original Image of Radar

```
Training on single CPU.
Initializing input data normalization.
|==========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|==========================================================================================================|
|       1 |           1 |       00:00:00 |       11.11% |       33.33% |       2.3277 |       2.7334 |          0.0100 |
|      30 |          30 |       00:00:02 |      100.00% |      100.00% |   2.7154e-06 |   2.8573e-05 |          0.0100 |
|==========================================================================================================|
Output of CNN Classifier is: GRAVEL
Final Validation Accuracy:
   83.3333
```

Fig 4.2.1 After Testing the original Image by using CNN was Gravel and its Accuracy

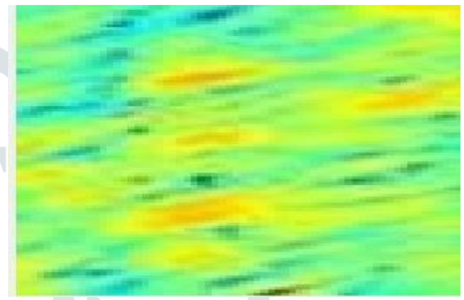

Fig 4.3 Original Image of Radar

Fig 4.3.1 After Testing the original Image by using CNN was MUD and its Accuracy

```
Training on single CPU.
Initializing input data normalization.
|==========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|==========================================================================================================|
|       1 |           1 |       00:00:00 |        5.56% |       50.00% |       2.4967 |       2.5973 |          0.0100 |
|      30 |          30 |       00:00:02 |      100.00% |      100.00% |   2.9855e-05 |       0.0528 |          0.0100 |
|==========================================================================================================|
Output of CNN Classifier is: MUD
Final Validation Accuracy:
   83.3333
```

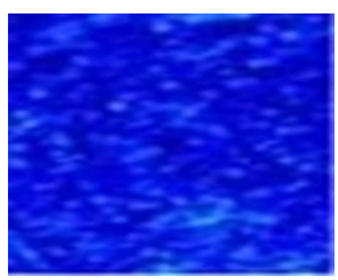

Fig 4.4 Original Image Of Radar

```
Training on single CPU.
Initializing input data normalization.
|=========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|=========================================================================================================|
|       1 |           1 |       00:00:00 |       16.67% |       33.33% |       2.9912 |       3.9531 |          0.0100 |
|      30 |          30 |       00:00:02 |      100.00% |      100.00% |   1.7962e-05 |       0.0039 |          0.0100 |
|=========================================================================================================|
Output of CNN Classifier is: RIVER
Final Validation Accuracy:
   83.3333
```

Fig 4.4.1 After Testing the original Image by using CNN was River and its Accuracy

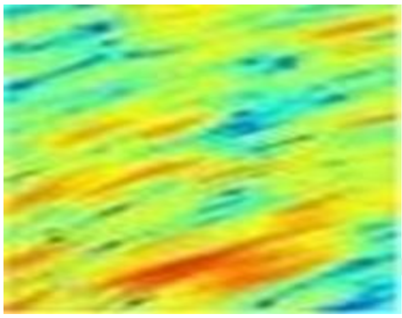

Fig 4.5 Original Image Of Radar

```
Training on single CPU.
Initializing input data normalization.
|=========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|=========================================================================================================|
|       1 |           1 |       00:00:00 |       22.22% |       66.67% |       1.9534 |       1.8589 |          0.0100 |
|      30 |          30 |       00:00:02 |      100.00% |       83.33% |   6.5038e-06 |       0.1751 |          0.0100 |
|=========================================================================================================|
Output of CNN Classifier is: ROCKY
Final Validation Accuracy:
   83.3333
```

Fig 4.5.1 After Testing the original image by using CNN the output was Rocky image and is accuracy

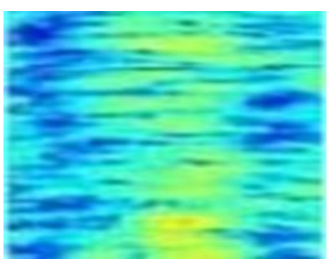

Fig 4.6 Original Image Of Radar

```
Training on single CPU.
Initializing input data normalization.
|=========================================================================================================|
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learning  |
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate       |
|=========================================================================================================|
|       1 |           1 |       00:00:00 |       27.78% |       50.00% |       2.5016 |       2.3362 |          0.0100 |
|      30 |          30 |       00:00:02 |      100.00% |      100.00% |   1.7966e-05 |       0.0656 |          0.0100 |
|=========================================================================================================|
Output of CNN Classifier is: UNEVEN
Final Validation Accuracy:
   83.3333
```

Fig 4.6.1 After Testing the original Image by using CNN was uneven and its accuracy

V. CONCLUSION:

It has been proposed to categorize surfaces using data that has been processed by 79 GHz imaging radar. Our findings suggest that by combining a 79 GHz scanning radar with subsequent image processing utilizing a convolutional neural network, great accuracy of surface identification may be attained. The radar's accuracy improves as its frequency is raised from 24 GHz to 79 GHz, since the microwave signal is more sensitive to the surface roughness at those higher frequencies.

These findings provide a solid basis for future research and development of a Surface ID system for use in automobiles. We hope to expand the current dataset by keeping an eye on roads in all kinds of weather using 300 GHz imaging radar in the near future (snow, rain, ice).

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