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Potholes Detection in Doppler Radar Signal's Power Spectral Density using Decision Tree

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ABSTRACT

Potholes are defects on the surface of roads, streets, or pavements brought on by depressions or holes, which are hazardous for vehicles and pedestrians, whether small divots or huge craters. Various methods have been explored to improve the accuracy of potholes detection. Existing approaches have advantages and disadvantages. This paper presents the proposed method of pothole detection utilising Doppler Radar signal's Power Spectrum Density (PSD) together with the Decision Tree classification algorithm. While continuous waveform (CW) radar is able to identify moving targets, it cannot localise the exact depth of the reflector, which is the prominent characteristic of potholes. In addition, the target's reflected signal is likely to be masked by nearby harmonics. Since the radar is moving despite the target of interest, mounting it on a moving vehicle offers a different perspective. This paper explores the potential of Doppler radar's signal for pothole detection while comparing two Machine Learning (ML) techniques. A commercially over-the-shelf (COTS) K-LC2 Doppler radar was employed to acquire pothole and non-pothole raw datasets. Doppler signal was hardly distinguished between pothole and non-pothole, either in the time or frequency domain. Hence, Doppler signals were converted to power spectral density (PSD), and PSD's features were extracted. Extracted features were applied with the coarse Decision Tree (DT) and K-Nearest Neighbours (KNN) classification algorithms. The result exhibits a better accuracy of 91.2% for 80:20 distribution by using the Decision Tree.

Keywords:
Decision tree; PSD; Doppler; Radar; Pothole

1. Introduction

In recent years, the field of transportation infrastructure has made significant strides towards improving road safety and durability. One critical aspect in this domain is the detection of road defects, such as potholes, which can pose substantial risks to both vehicles and road users. Potholes,

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often caused by wear and tear, adverse weather conditions, and heavy traffic, can lead to accidents, vehicle damage, and increased maintenance costs. Timely and accurate detection of potholes is imperative for proactive maintenance and improved road safety.

Potholes, depressions in road surfaces caused by deteriorated asphalt and weakened underlying soil, pose significant challenges to road users and governmental authorities worldwide. The adverse effects of potholes range from compromised road safety and increased vehicle maintenance costs to financial liabilities for government agencies. Therefore, the development of efficient and accurate methods for pothole detection and timely repair is crucial.

The significance of pothole detection and remediation cannot be overstated. According to a collaborative effort between the Malaysian government and Waze, approximately 50,000 potholes were reported in the state of Selangor alone between 2019 and 2020 [1]. Malaysia, ranked as the 12th country with the worst roads globally [2], has witnessed a steady decline in road quality, resulting in a high number of road fatalities. Moreover, the responsibility of maintaining roads falls on governmental bodies like the Malaysian Public Works Department (JKR) and local authorities, who may face compensation claims due to negligence in managing potholes [3]. Syahmi Radzi *et al.,* [4] studied the road characteristics effect over motorcycle crashes fatality involving the heavy good vehicle (HGV). The research provides a new insight on the importance to understand the characterisation of road such road defect, quality surface, type and condition, and their effect on crashes; Thus, the severity can be reduced. Hence, exploring innovative approaches for efficient pothole detection is imperative to mitigate these issues.

Research in road defect detection has explored various sensing technologies to address this challenge. Various sensor types have been investigated for pothole detection, such as vision-based, laser-based, microwave-based, acoustic-based and vibration-based. Each has advantages and limitations. Vision and laser-based sensors often have limited views over range, weather, and lighting conditions. Meanwhile, the acoustic sensor provides a cost-effective solution but has difficulty distinguishing obstacles. In addition, vibration-based sensor faces challenges in detecting minor defect and has battery consumption limitations. Hence, advancements in sensing technologies, such as radar systems, coupled with the power of deep learning algorithms, have shown great potential in addressing this issue.

Limited knowledge exists regarding the efficacy of classifying Doppler radar waveforms associated with potholes. Doppler radar can ascertain a target's velocity but cannot determine its specific depth, making it unsuitable for depth-based pothole detection [5]. Furthermore, surrounding elements often obscure echoes from the target of interest [5,6]. This depth detection limitation in Doppler radar, as seen in ultrasound medical imaging, has been discussed by X. Li *et al.,* Their work explores how factors like ultrasound beam characteristics and intonation angle affect depth precision and underscores the importance of spatial resolution for distinguishing closely spaced structures at various depths. These complexities highlight the challenge of accurately detecting pothole depths using Doppler radar [6].

Furthermore, the effectiveness of a classification is determined by how many waveforms can be distinguished as belonging to a category described by a class. Moreover, the time-domain signal and frequency spectrum are insufficient to differentiate between potholes and non-pothole Doppler signals over asphalt pavement, which leads to incorrect interpretation. Therefore, this study examines the categorisation relevance of classification to reflect on the potential of Doppler radar signal sensing. Additionally, the effectiveness of the coarse Decision Tree (DT) and K-Nearest Neighbours (KNN) for classifying Doppler waveforms is compared.

1.1. Radar-Based Road Defects Detection

Detecting damages along the inspected road and identifying cracks promptly are crucial for enhancing the thorough monitoring and assessment of road pavement conditions [7]. Millimetre-wave (mmWave) radar technology has proven its prowess in pothole detection research. Wu, H., Qi, F., and Wang, J.'s work introduced a low-terahertz radar system operating at 94GHz, employing the frequency-modulated continuous-wave (FMCW) technique with a 3mm wavelength [8]. Through extensive simulations and experiments, this system demonstrated its effectiveness in detecting road pits and smaller obstacles like rocks and steel balls. Simulations consistently reveal higher electric field strength within road pits compared to the road surface, regardless of pit depth, and experimental results confirmed a distinctive 16 dB field strength difference. However, the work only explored the FMCW signal, which can identify the pothole depth.

Additionally, A. Srivastava *et al.,* [9] research employed the finite difference time domain (FTDT) techniques to estimate the 2D Radar Cross-Section (RCS) of potholes, highlighting the substantially higher RCS values (approximately 20dB) in potholes filled with air or rainwater compared to flat road surfaces. They emphasised the influence of dielectric constants on RCS, particularly in potholes with triangular cross-sections. The study focused on the automotive radar frequency, also exploring utilising the look-ahead radar for prior sensing, contrary to Doppler-radar principle.

Moreover, Valuyskiy, D. V. *et al.,* [10] study developed a 77GHz radar bench to investigate reflection properties and build mathematical models for various obstacles, including fallen trees and potholes. This research encompassed hardware and software tool development for recording and analysing reflections, with the overarching aim of enhancing obstacle detection algorithms in Advanced Driver Assistance Systems (ADAS) radar modelling.

In a separate contribution, Soroush Ameli's proposal [11] introduced a radar-based system for autonomous vehicles, leveraging mmWave technology for precise road sensing in driverless cars, achieving notable accuracy in classifying road conditions, and holding potential applications in stabilisation, path planning, and guidance control systems. Collectively, these studies underscored the growing significance of mmWave radar in advancing pothole detection research and its broader potential for improving road safety and autonomous vehicle technology. Similar to the earlier work, this research also implemented the FMCW.

These studies [6-9] have provided valuable insights into using mmWave radars, offering guidance on operating radar modules for pothole detection and optimal mounting placements on vehicles for radar data collection. However, it's important to note that while these studies enlightened the pothole detection, such as using RCS and the reflection properties of signals from specific obstacles, they did not address Doppler-based parameters and measurements for pothole sensing. This revealed a gap that warrants further exploration and consideration in future research efforts.

Conversely, numerous studies have underscored the versatile applications of Ground-Penetrating Radar (GPR) in pothole detection and pavement assessment. For instance, X. Liang *et al.,* [12] harnessed 3D-GPR and the VGG16 machine learning model to detect pavement distress efficiently. At the same time, Cao Q. and Al-Qadi I.L. [13] studied the GPR's potential in identifying inadequate bonding in asphalt overlays, accentuating its sensitivity to texture and moisture variations. Meanwhile, Li, S. *et al.,* [14] introduced automation to conceal crack detection through 3D GPR and YOLOv4, and Gao J. *et al.,* [15] achieved real-time pavement distress detection using GPR and Faster R-ConvNet. Torbaghan M. E. *et al.,* [16] improved road crack detection with GPR, and L. Zhao *et al.,* [17] explored GPR's capacity in non-contact terrain sensing. These studies shed light on GPR's adaptability and effectiveness in assessing road infrastructure, including pothole detection.

While these studies offered valuable insights into GPR's operation and potential, they primarily focused on its versatility in detecting road defects such as pavement distress and asphalt debonding. Notably, they delved into radar feature extraction but did not specifically address Doppler-based features. Hence, this highlights the need for further research to evaluate and compare Doppler-based techniques with existing pothole detection infrastructure, potentially enriching our understanding of radar technology's capabilities.

In summary, the research focused on pothole sensing using radar has yielded promising results. These studies have demonstrated the potential of radar technology to detect and analyse potholes effectively. However, many aspects of radar feature extraction, named Doppler-based features have not been discussed, stressing the need for such a study to compare the feasibility with existing infrastructure.

1.2. Utilisation of Doppler Information in Road Defect Detections

Several studies have explored the work of pothole detection, focusing on leveraging Doppler-based information. In one notable contribution, D. A. Jordan and colleagues [18] tackled the pressing issue of potholes in African road networks by introducing the Pothole Detection, Classification, and Logging (PDCL) system. This innovative system ingeniously amalgamates active infrared stereo vision and mmWave FMCW radar sensors, all mounted on a vehicle's bonnet. While the radar's range-Doppler maps (RDMs) faltered in detecting potholes due to their diminutive radar cross-sections, the stereo vision component emerged as the hero of the day. It accomplished the detection of shallow potholes by flattening depth maps to accentuate deviations in the road surface. This work was a testament to the inefficacy of RDMs generated using FMCW radar and champions the superior efficacy of stereo vision in Doppler-based pothole detection.

In a related exploration, B. S. M. Aparajith, A. Srikanth, A. Ali, and T. S. Chandar [19] scrutinised radar technology, specifically FMCW and Orthogonal Frequency Division Multiplexing (OFDM) radar methodologies, in the pursuit of spotting low-height road surfaces anomalies such as humps and potholes. Their investigation centred on the estimation of RCS and the subsequent identification of these anomalies. Doppler-based features played a pivotal role in their approach, manifesting in two distinct ways. First, Range-Doppler (RD) processing was used to determine the radial speed of targets that were discovered by using the Doppler shift in the received radar signal. Secondly, in the OFDM methodology, Doppler-induced phase progression across consecutive OFDM symbols was leveraged for velocity estimation, mirroring the principles of FMCW radar systems.

Employing the Logistic Regression Machine Learning algorithm, this classification model achieved impressive results, boasting a training accuracy of 84.4% and a test accuracy of 80%. This investigation not only sheds light on radar-based target detection, but also showcased the potential of Doppler-based velocity estimation and classification techniques in road surface anomaly detection, with prospective applications in real-time traffic management and safety systems.

Turning attention to the domain of autonomous vehicles, Z. Xu, C. J. Baker, and S. Pooni [20] endeavoured to enhance radar technology, with a prominent focus on exploiting Doppler-based features to bolster obstacle detection capabilities. Their research unveiled an advanced algorithm that adeptly surmounted the challenge of accurately distinguishing between moving and stationary objects across diverse scenarios. Notably, this study elucidated that these Doppler-based radar features could be effectively repurposed for pothole detection, contributing not only to road safety but also to improved ride quality, while simultaneously augmenting the autonomous driving capabilities of vehicles.

Yet another pioneering endeavour in road defect detection is the work by I. Katsamenis and colleagues [21], which embraced Unmanned Aerial Vehicles (UAVs) and the YOLOv5 deep learning model. This study stands out due to its unwavering emphasis on Doppler-based features within the YOLOv5 model, enriching defect detection accuracy. By detecting frequency shifts in radar or sensor data induced by moving objects, such as vehicles on the road, this research imbued the model with the unique ability to distinguish static road defects from moving objects. The incorporation of Doppler information facilitated the precise localisation of road defects within captured images, effectively discerning between anomalies like cracks and potholes and other mobile elements like vehicles. This innovative approach showcases the potential of integrating Doppler features into vision-based sensors for pothole detection, pushing the boundaries of technological capability in this field.

All of the earlier works studied various techniques which mostly using doppler information of FMCW signal, but did not address the CW Doppler radar utilisation. In contrast to the aforementioned studies, this paper focuses on practical applications of commercially available 24 GHz K-LC2 RFbeam radar modules for road pavement pothole detection. It explores the untapped potential of CW Doppler signals in assessing road surface conditions, in conjunction with a decision tree classification algorithm. This study holds significance as it presented the capability of Doppler-based research in improving efficient and reliable road defect detection methods, promising safer and more durable transportation infrastructure.

2. Methodology

2.1 Experimental Setup for Signal Acquisition

The experimental setup of potholes detection was conducted on several pothole and non-pothole pavements, utilizing a 24 GHz K-LC2 RFbeam radar module [22]. The commercially of the shelf (COTS) doppler radar is a 2x4 patch, maximum at 15dBm of equivalent isotropic radiated power (EIRP). The transceiver was operating at 24.125 GHz with 3 dB beamwidth of horizontal 80^o and vertical 34^o. Figure 1 presents the radar module utilized.

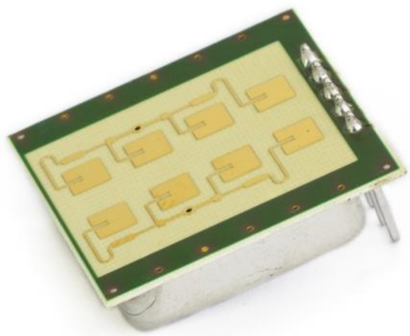


Fig. 1. Radar module utilised for data acquisition (K-LC2 by RFbeam [22]

The K-LC2 radar module was integrated to RFbeam ST100 enabling a connection to acquisition software, RFbeam SignalViewer, through a USB cable. Figure 2 displays the radiation pattern of the patch antenna.

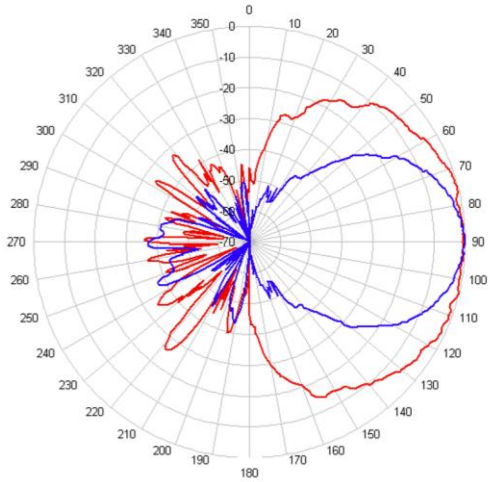


Fig. 2. K-LC2 module antenna patch radiation pattern [22]

The module was mounted in front of the vehicle at a 1-meter height with an angle of 45°. In this study, a sedan car was used. Figure 3 is the setup for data acquisition.

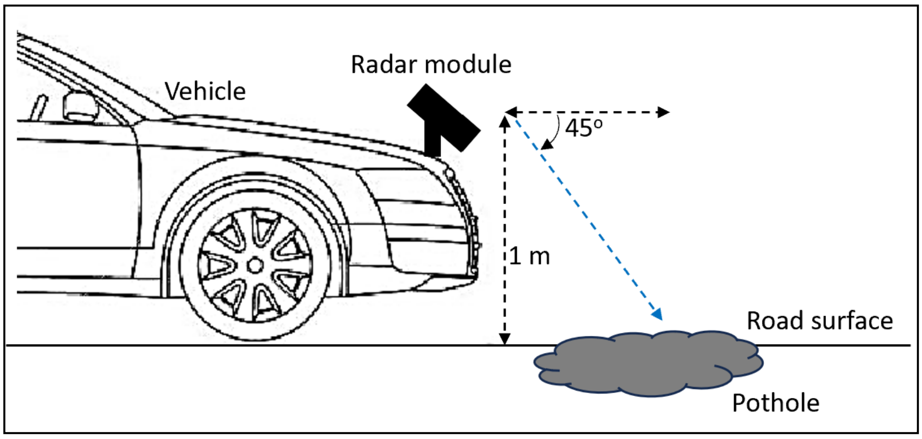


Fig. 3. Data acquisition setup

Figure 4 depicts examples of potholes which raw Doppler signals acquired for the study. A CW Doppler radar operates to capture any movement observed. However, in this work, we proposed that the radar be mounted and, on the move, to acquire signals from static roads and potholes.

Fig. 4. Example of potholes measured during experiments

2.2 Doppler Signal Processing

The block diagram of the study is illustrated in Figure 5. A raw signal received was recorded in the *.wav format. The signal was extracted by using MATLAB R2022b to a readable value in the time domain. Each signal was sliced into 10,000 sample points to ensure the power magnitude of the frequency spectrum can be compared equally between potholes and non-potholes. Data for potholes and non-potholes were segmented manually. There were 460 datasets consisting of potholes and non-potholes. Signals were post-processing, which was not using real-time processing. Next, the time domain waveform was transformed to a power spectral density (PSD) in the frequency domain of 256 discrete Fourier transform (DFT) points.

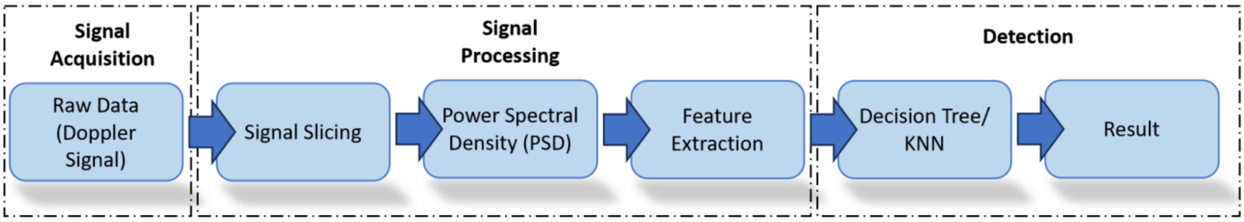


Fig. 5. Block diagram the proposed of pothole detection

Thirteen features (excluding Class) from the PSD were extracted and applied with algorithms for classification. In this work, DT and KNN Machine Learning (ML) techniques were employed. Features were extracted as tabulated in Table 1 for the classification purposes. All signal processing and ML were conducted using MATLAB.

Table 1
Feature extracted form PSD

Features list	Feature ID
Mean value of PSD magnitude	Mean
Maximum value of PSD magnitude	Max
Minimum value of PSD magnitude	Min
Median value of PSD magnitude	Median
Mean square error of PSD magnitude	MSE
Root means square error of PSD magnitude	RMSE
Scattering Index	SI
Mean distance of peaks location	MeanCycle
Minimum distance of peaks location	MinCycle
Maximum distance of peaks location	MaxCycle
Distance between the first and second highest peaks	MaxDiff
Distance between the highest and the lowest peaks	MaxPeakDistHL
Distance between first and last peaks	DistancePeakEE
Pothole or non-pothole categories	Class

2.3 Potholes Classification

PSD extracted features were exported and applied with the DT and KNN classification algorithms, which are supervised learning techniques. DT is a simple tree-structured classifier consisting of root, decision, and leaf nodes. It is easy to comprehend as it typically reflects human's thinking. In this analysis, coarse DT was utilised due to its higher flexibility. Next, a similar dataset was also applied with coarse KNN. Like DT, KNN is a non-parametric method and one of the easiest ML techniques.

KNN works in such a way that it explores the k-neighbours and produces the projection. The course KNN was applied to avoid rigid distinction between classes with 100 neighbours.

A cross-correlation was applied to avoid overfitting, and the Principal Component Analysis (PCA) was disabled. Dataset fed contained 34.57% pothole data and 65.43% non-pothole data, out of 460. Non-potholes consisted of even and uneven pavement surfaces, which were classified as one. The classification was conducted with 80:20 ratio.

3. Results and Discussion

3.1 Short-Time Fourier Transform Analysis

Firstly, the Doppler signal was processed using the Short-Time Fourier Transform (STFT) to observe the signal's frequency content over time. Figure 6 shows:

i. doppler signal in time domain of a pothole
ii. spectrogram of the doppler signal for pothole
iii. doppler signal in time domain of a non-pothole
iv. spectrogram of the doppler signal for non-pothole.

In both scenarios, it was hard to distinguish between potholes and non-potholes. Both exhibit a continuous signal with non-uniform magnitudes for the time domain Doppler signals. Subsequently, the STFT spectrogram also presents spikes indicating intensity at certain parts of the signal. Therefore, STFT analysis was not competent to distinguish between pothole and non-pothole signals.

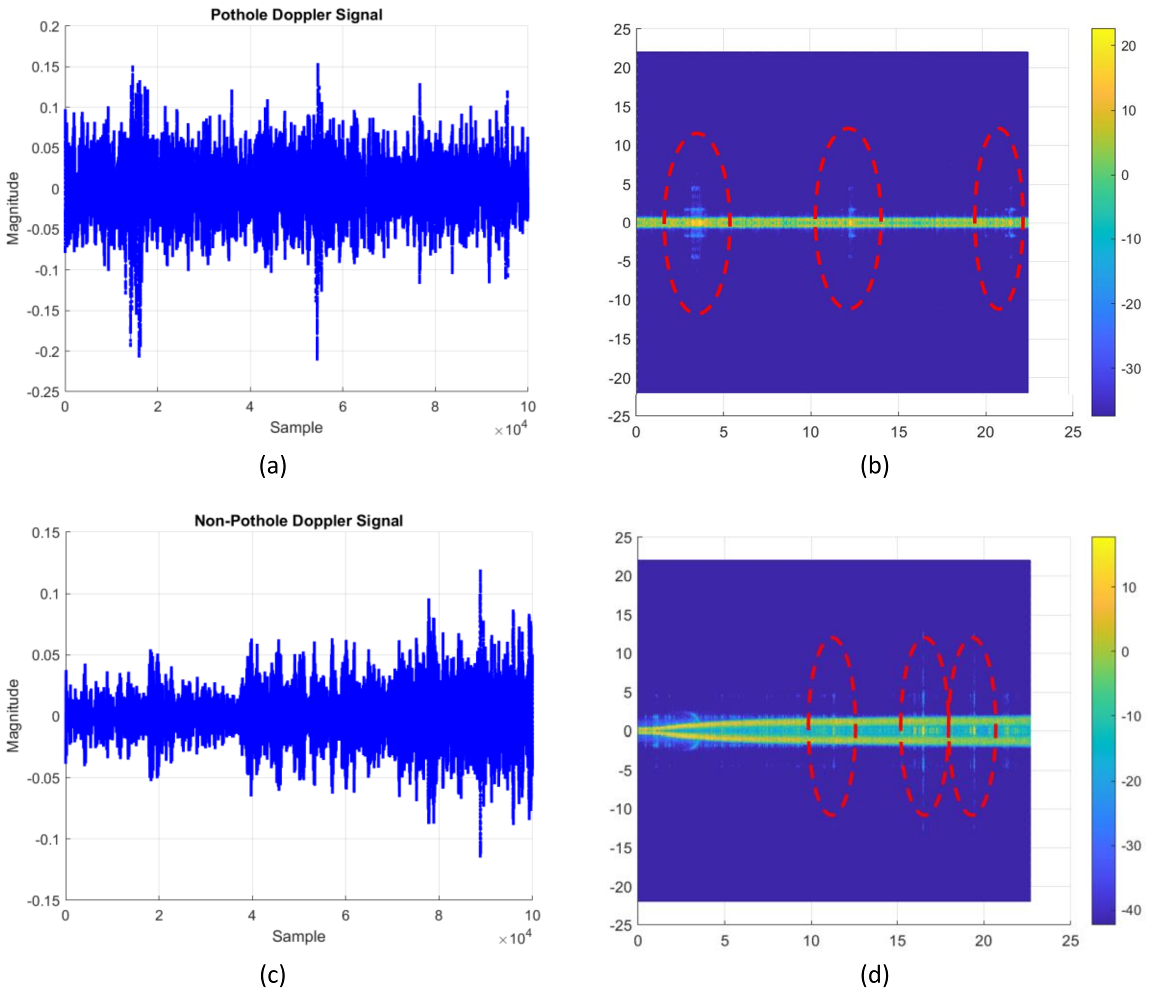


Fig. 6. Example of doppler signal for (a) a pothole in time domain, (b) spectrogram of pothole signal, (c) a non-pothole in time domain, and (d) spectrogram of non-pothole signal

3.2 Power Spectrum Density Analysis

Signals were further analysed in the frequency domain by transforming to Welch's power spectrum density (PSD) with 256 discrete Fourier transform (DFT) points. Welch's approach lowers noise in the estimated power spectra, improving the standard periodogram spectrum. Figure 7 presents several examples of pothole PSD, and Figure 8 displays examples of non-pothole PSD.

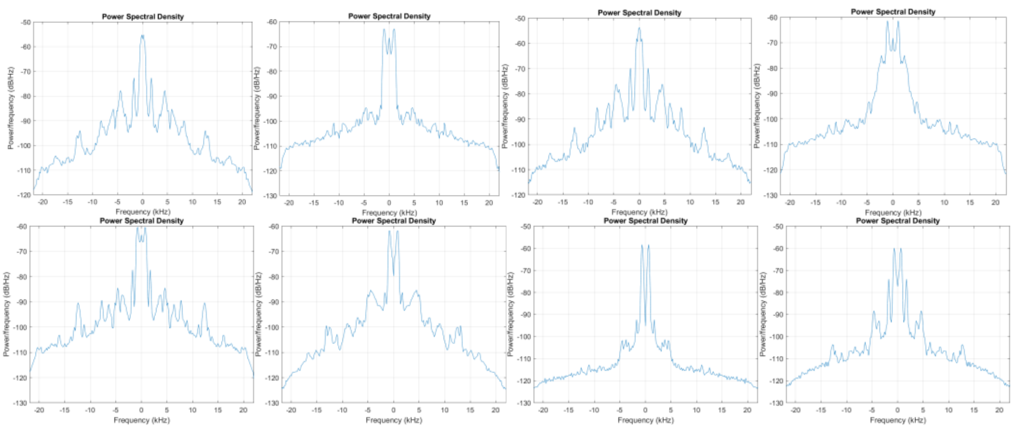


Fig. 7. Example of potholes PSD

Restate, a signal was manually segmented with 10,000 sample points prior to PSD to obtain results as per Figures 7 and 8. PSD result demonstrates a better behaviour of Doppler signal, between magnitude and frequency. However, peak behaviour for both cases was unable to be categorised by using a simple peak distinction technique such as maximum peak. Overall, visually determining between these signals in time or frequency domains was difficult. Therefore, PSD features for each spectrum were extracted, as tabulated in Table 1, for further analysis using DT and KNN algorithms.

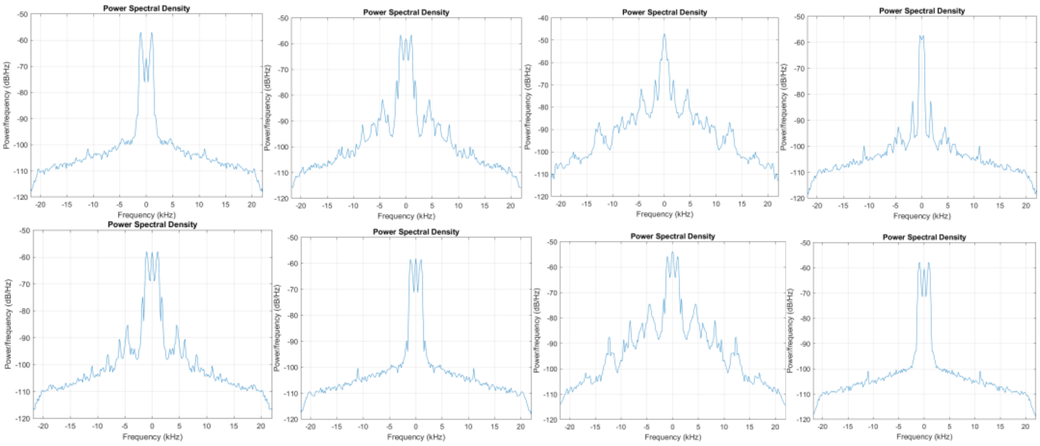


Fig. 8. Example of non-potholes PSD

3.2.1 Potholes classification

Features utilised for this experiment are as per Table 1. The classification techniques employed were coarse DT and KNN, the most flexible model for both methods. Table 2 indicates the performance comparison between these two models. The coarse DT had a maximum number of splits of 4 using Gini's diversity index. Meanwhile, the coarse KNN had 100 neighbours with Euclidean distance metric and equal distance weight.

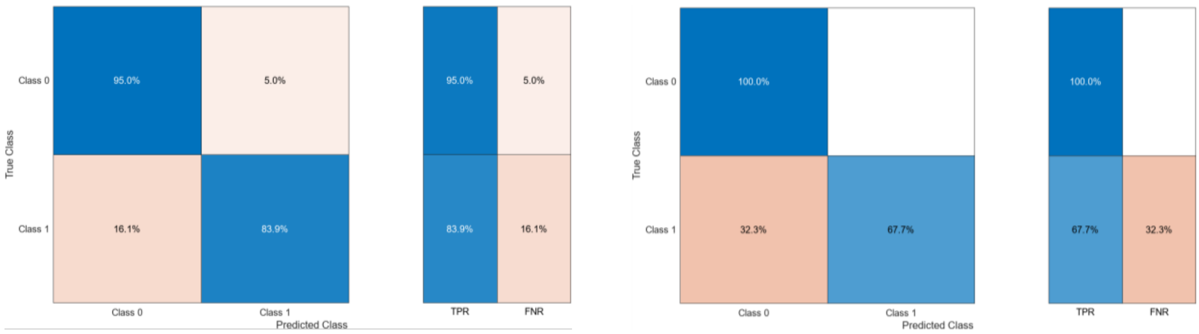
Table 2
Comparison between coarse DT and KNN algorithms

Performance	DT	KNN
Training results:		
Accuracy (Validation), *%*	90.5	81.8
Prediction speed, *obs/ sec*	~10,000	~3,900
Training time, *sec*	8.5287	8.1995
Test results:		
Accuracy (Test), *%*	91.2	89.0

From the table, DT outperforms KNN for validation and testing, which are 90.5% and 91.2%, respectively, for the 80:20 distribution. KNN's accuracy is 8.7% less than DT during validation and 2.2% less during testing. Due to the large data size, DT exhibits higher prediction speed and training time. Besides, KNN is known for its effectiveness on small data.

The coarse DT and KNN test confusion matrix is as per Figure 9. From the matrix, it describes that for DT, Class 1 (pothole) has 83.9% true positive rates (TPR) and 16.1% false negative rates (FNR). On the other hand, Class 0 (non-pothole) has 95.0% TPR and 5.0% FNR. FNR for Class 1 is at 16.1%, which is higher than Class 0 at 5.0%, indicating more pothole's Doppler signals are wrongly predicted compared to Class 0.

Meanwhile, the KNN matrix presents 100% of non-pothole TPR. Hence, it was able to be fully classified. However, pothole produces 67.7% TPR and 32.3% FNR. It displays a higher confusion of pothole detection when using the KNN algorithm. Improvement by 16.2% was observed over the classification of Class 1 when DT is applied, with a trade-off of 5.0% over the classification of Class 0. The exercise displays that accuracy increases with the DT technique.



(a) (b)

Fig. 9. Test confusion matrix (a) DT, and (b) KNN

4. Conclusions

This study established an analysis using the coarse model of DT and KNN techniques for pothole detection by utilising a Doppler radar signal. The study was conducted over actual raw data acquired for potholes and non-potholes. The work contributes to the improvement of pothole detection by applying a DT classification over the Doppler signal PSD's attributes, which produced 91.2% accuracy at an 80:20 dataset ratio. The classification was also compared to the KNN algorithm. The KNN presents slightly low accuracy but better prediction speed and training time. From observation, visual of Doppler signals in the time domain, STFT, and PSD plots were hard to be classified between pothole and non-pothole. Hence, the decision was to employ ML over the PSD features extracted. The finding lays a baseline for Doppler radar signal processing and detection. More validation can be explored using other machine learning (ML) and deep learning (DL) approaches to pothole detection performance.

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