<https://www.sciencedirect.com/science/article/pii/S2214317320302067>

The paper explores insect classification and detection in field crops using modern machine learning techniques, addressing challenges in traditional identification methods. Experiments utilize shape features and machine learning algorithms such as artificial neural networks (ANN), support vector machine (SVM), k-nearest neighbors (KNN), naive bayes (NB), and convolutional neural network (CNN) on Wang and Xie datasets. An insect pest detection algorithm employing foreground extraction and contour identification is proposed for complex backgrounds. The CNN model achieves the highest classification rates of 91.5% and 90% for nine and 24 class insects, respectively. The detection algorithm exhibits efficient performance with reduced computation time. The study emphasizes early insect detection for enhanced crop yield and quality, comparing favorably against state-of-the-art algorithms. The methodology involves image pre-processing, augmentation, and shape feature extraction, with classification using ANN, SVM, KNN, NB, and CNN models. The work showcases effectiveness in agriculture field insect detection and classification, particularly in the early stages of crop growth.

<https://www.researchgate.net/publication/237078843_EARLY_DETECTION_AND_MONITORING_OF_RED_PALM_WEEVIL_APPROACHES_AND_CHALLENGES>

visual inspection

<https://pdfs.semanticscholar.org/2072/9832288d874f443d2fc861cbf94f6293c969.pdf>

the use of vibroacoustic recorders placed on trees to collect short clips of internal vibroacoustic sounds. These recordings are then wirelessly transmitted to cloud services, where deep learning networks analyze the data to determine if a tree is infested by wood-boring insects. The emphasis is on using vibroacoustic monitoring and deep learning techniques, not radar frequency, to assess the infestation state of trees.

<https://www.sciencedirect.com/science/article/pii/S0307904X23000045>

to identify pulse-like ground motions in seismic recordings, specifically near-fault multi-pulse ground motion. The study aims to develop a method for effectively identifying single- and multi-pulse ground motions using the Generalized Continuous Wavelet Transform (GCWT). The identified pulses in seismic recordings can provide insights into seismic source characteristics and help in seismic risk analysis for structures

<https://ieeexplore.ieee.org/document/8742645>

used radra data to detect the tree internal structure but needs subscription or access

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10272373/>

the impact of climate change on forests and the use of machine learning (ML) techniques, robotic platforms, and artificial vision systems for remote monitoring of forest health. Leveraging UAVs with various sensors, including LiDAR and cameras, researchers estimate crucial parameters such as canopy cover, vegetation indexes, and disease detection

<https://arxiv.org/pdf/2203.06553>

uses radar data but visual radar data ,pontnet++

<https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/sil2.12103>

the paper discusses Frequency Diverse Array (FDA) radar, which is a type of radar system, no mention of data science

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7999239/>

radar data in the context of object detection and classification, particularly for advanced driver-assistance systems (ADAS) and autonomous vehicle applications.

<https://www.imec-int.com/en/articles/imec-builds-world-s-first-spiking-neural-network-based-chip-for-radar-signal-processing>

a chip developed by Imec that processes radar signals using a spiking recurrent neural network (SNN). This chip is designed to consume significantly less power than traditional implementations and has a tenfold reduction in latency, making it suitable for applications such as anti-collision radar systems for drones.

<https://www.mathworks.com/videos/target-detection-and-classification-in-radar-point-cloud-with-mathworks-1622075690538.html>

visual radar data treated by using point clouds, classification, clustering algorithms

<https://in.mathworks.com/help/radar/ug/radar-target-classification-using-machine-learning-and-deep-learning.html>

This example shows how to classify radar returns with both machine and deep learning approaches. The machine learning approach uses wavelet scattering feature extraction coupled with a support vector machine. Additionally, two deep learning approaches are illustrated: transfer learning using SqueezeNet and a Long Short-Term Memory (LSTM) recurrent neural network. Note that the data set used in this example does not require advanced techniques but the workflow is described because the techniques can be extended to more complex problems.

<https://ietresearch.onlinelibrary.wiley.com/doi/full/10.1049/iet-rsn.2019.0331>

the research employs signal processing techniques, feature extraction from radar signals, and machine learning classification algorithms to achieve accurate classification of radar signals. skewness and kurtosis features play a significant role in the proposed method's success. The use of SVM and KNN classifiers, along with comparisons with other methods, provides insights into the effectiveness of the proposed approach

<https://towardsdatascience.com/classification-of-radar-returns-c79fa1ce42eb>

radar returns from the ionosphere, and the goal is to classify these returns into "good" or "bad" categories for further analysis.

Data Preprocessing and Exploratory Data Analysis (EDA):

Preliminary EDA involves converting the dataset into a pandas dataframe, removing duplicate rows, and normalizing the data using MinMaxScaler.

Probability density function (PDF) and cumulative density function (CDF) plots are used to analyze feature distributions.

Heat maps for the correlation matrix help identify overlapping features.

Dimensionality reduction techniques, including SelectKBest, PCA, and t-SNE, are employed to gain insights into feature importance and data structure.

Architectures:

Different machine learning models are explored, starting with Linear Support Vector Machine (SVM) and later moving to Gradient Boosted Decision Trees (GBDT) using CatBoostClassifier.

A Multilayered Perceptron (MLP) neural network is implemented, outperforming other models with an accuracy of 98% on the test dataset.

<https://in.mathworks.com/help/radar/ug/radar-and-communications-waveform-classification-using-deep-learning.html>

radar frequency data for waveform classification using deep learning techniques. The approach involves generating radar waveforms with different modulation types, simulating various impairments, and then using a deep convolutional neural network (CNN) for classification. The classification is performed based on time-frequency features extracted using the Wigner-Ville distribution (WVD).

<https://in.mathworks.com/help/radar/ug/radar-and-communications-waveform-classification-using-deep-learning.html>

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<https://link.springer.com/chapter/10.1007/978-3-319-26450-9_5>

the application of neural network (NN)-based approaches for the identification and classification of radar signals. The goal is to detect and classify radar signals in real-time for threat detection, avoidance, and situation awareness.

Algorithm approaches used : neural networks

training the neural networks on labelled data

dimensionality reduction : PCA (Principal Component Analysis)

<https://www.mathworks.com/videos/target-detection-and-classification-in-radar-point-cloud-with-mathworks-1622075690538.html>

article not yet included

<https://ieeexplore.ieee.org/document/8706004>

classify objects using raw radar data and convolutional neural networks (CNNs).

<https://onlinelibrary.wiley.com/doi/book/10.1002/9781118956878>

radar data procesing with applications

<https://www.amazon.com/Learning-Communications-Automatic-Target-Recognition/dp/163081637X>

radio frequency automatic target detection using deep learning

<https://link.springer.com/chapter/10.1007/978-3-031-31435-3_23>

not yet included

<https://www.sciencedirect.com/science/article/abs/pii/S0952197623008643>

uses yolov3 for visual radar frequency data for target detection

**MY OBSERVATIONS FROM ALL THE PAPERS :**

Radar data is utilized in various ways for different applications in the context of data science and machine learning. Here's a breakdown of the common approaches for signal processing, feature extraction, and classification used in these studies:

**Signal Processing Approaches:**

**1)Vibroacoustic Monitoring:**

**Application:** Monitoring wood-boring insect infestation in trees.

**Technique:** Vibroacoustic recorders placed on trees to collect internal vibroacoustic sounds.

**Analysis:** Deep learning networks analyze the data for infestation determination.

**2)Seismic Recordings:**

**Application:** Identifying pulse-like ground motions in seismic recordings.

**Technique:** Generalized Continuous Wavelet Transform (GCWT) to identify single- and multi-pulse ground motions.

**Analysis:** Provides insights into seismic source characteristics and aids in seismic risk analysis.

**3)UAVs and Remote Sensing:**

**Application:** Monitoring forest health in the context of climate change.

**Technique:** UAVs equipped with LiDAR and cameras for data collection.

**Analysis:** Machine learning techniques and artificial vision systems for estimating parameters such as canopy cover, vegetation indexes, and disease detection.

**4)Object Detection for ADAS:**

**Application:** Object detection and classification for advanced driver-assistance systems (ADAS) and autonomous vehicles.

**Technique:** Utilizes radar data for object detection and classification.

**5)SNN for Radar Signal Processing:**

**Application:** Anti-collision radar systems for drones.

**Technique:** Uses a spiking recurrent neural network (SNN) to process radar signals.

**Advantage:** Significant reduction in power consumption and latency.

**Feature Extraction Approaches:**

**1)Machine and Deep Learning Approaches:**

**Application:** Classifying radar returns.

**Techniques:**

**Machine Learning:** Wavelet scattering feature extraction with a support vector machine.

**Deep Learning:** Transfer learning using SqueezeNet and a Long Short-Term Memory (LSTM) recurrent neural network.

**2)Insect Classification in Crops:**

**Application:** Insect classification and detection in field crops.

**Techniques:**

Shape features and machine learning algorithms (ANN, SVM, KNN, NB, CNN).

Image pre-processing, augmentation, and shape feature extraction.

**Note:** CNN achieves high classification rates.

**3)Ionospheric Radar Data:**

**Application:** Classifying radar returns from the ionosphere as "good" or "bad."

**Techniques:**

**Data Preprocessing:** Conversion to pandas dataframe, duplicate removal, normalization.

**Exploratory Data Analysis:** PDF, CDF plots, heat maps, dimensionality reduction (SelectKBest, PCA, t-SNE).

**Machine Learning Models:** Linear SVM, GBDT using CatBoostClassifier, MLP neural network.

**4)Radar Waveform Classification:**

**Application:** Classifying radar frequency data for waveform classification.

**Techniques:**

Waveform generation with different modulation types and impairments.

Wigner-Ville distribution (WVD) for time-frequency feature extraction.

Classification using a deep convolutional neural network (CNN).

**Classification Algorithms:**

**1)Insect Classification in Crops:**

**Algorithms:** ANN, SVM, KNN, NB, CNN.

Note: CNN achieves the highest classification rates.

**2)Ionospheric Radar Data:**

**Machine Learning Models:** Linear SVM, GBDT using CatBoostClassifier.

**Neural Network:** Multilayered Perceptron (MLP) with 98% accuracy on the test dataset.

**3)Radar Waveform Classification:**

**Machine Learning Approach:** Support Vector Machine (SVM).

**Deep Learning Approaches:** Transfer learning using SqueezeNet, Long Short-Term Memory (LSTM) recurrent neural network.

**Common Themes:**

**Data Preprocessing and EDA:** Several studies involve converting data into pandas dataframes, removing duplicates, and normalizing data. EDA includes PDF, CDF plots, and heat maps.

Probability density function (PDF) and cumulative density function (CDF) plots are used to analyze feature distributions.

**Dimensionality Reduction:** Techniques such as PCA, t-SNE, and SelectKBest are used to gain insights into feature importance.

**Deep Learning:** CNNs and LSTMs are frequently employed for classification tasks, demonstrating high accuracy.

**Considerations:**

The choice of techniques often depends on the specific application and nature of the data.

**MY RESEARCH ON WHICH ARE ACTUALLY AAPPLICABLE APPROACHES TO THE NATURE OF OUR DATA**

are cnns and lstm used for numeric radar data or visual radar data?

CNN’S AND LSTM ARE SUITABLE ONLY WHEN   
radar data is already in visual form or 2d form or time-series or matrix or images mostly

**Nature of our data :**

Our data is in a tabular format with numerical features, in a structured data form rather than an image or sequence. For structured data, traditional machine learning models and shallow neural networks (MLPs) are more suitable than CNNs or LSTMs.

**Steps we can follow for our radar frequency data :**

**Data Preprocessing:**

Ensure that our data is properly preprocessed, including handling missing values, scaling, and normalizing the features.

**Exploratory Data Analysis (EDA):**

statistical measures to understand the distribution of features.

include mean, median, standard deviation, skewness, and kurtosis.

correlation matrices to identify relationships between different features.

data visualization techniques like histograms, box plots, and scatter plots to visually analyze the data distribution and identify outliers.

**FEATURE EXTRACTION RESEARCH:**

Frequency-domain features involve Fourier transforms or other signal processing methods.

Feature selection methods, such as SelectKBest, can help identify the most informative features for classification task.

**Model Selection:**

our data is structured,

traditional machine learning models such as Decision Trees, Random Forests, Support Vector Machines (SVM),KNN or Gradient Boosted Trees.

Experiment with shallow neural networks (MLPs) as they can handle structured data.

Pytorch, tensorflow, keras

**Ensemble Methods:**

ensemble methods like bagging or boosting to improve model performance.

**Bagging :**

Bagging is an ensemble learning technique that aims to improve the stability and accuracy of machine learning algorithms. It involves training multiple instances of the same learning algorithm on different subsets of the training data. These subsets are created by random sampling with replacement, known as bootstrapping. After training, the predictions from each model are combined, often by averaging (for regression) or voting (for classification), to obtain a final prediction. Bagging helps reduce overfitting and variance, particularly in models that are sensitive to the training data.

**Boosting:**

Boosting is another ensemble learning technique that combines multiple weak learners (models that perform slightly better than random chance) to create a strong learner. Unlike bagging, boosting focuses on sequentially training models, where each new model corrects the errors of its predecessor. Instances in the dataset are assigned weights, and misclassified instances receive higher weights. The subsequent models pay more attention to these misclassified instances, leading to a refined model with improved performance. Boosting is effective for reducing bias and can lead to high accuracy, but it is more prone to overfitting compared to bagging. Popular boosting algorithms include AdaBoost, Gradient Boosting, and XGBoost.

**SVM**

**Cons:**

**Computational cost:** Training SVMs can be computationally expensive, especially for large datasets.

**Parameter tuning can be complex:** Choosing the right parameters for an SVM can be challenging and impact performance significantly.

**Not ideal for non-linear problems**: SVMs work best for linearly separable data. More complex relationships might require different algorithms.

**KNN**

**Cons:**

**Curse of dimensionality:** KNN performance deteriorates with increasing data dimensions, potentially limiting its use for high-dimensional radar data.

**Computational cost for large datasets:** While efficient for small datasets, KNN can become computationally expensive for large-scale radar data analysis.

**Sensitive to noisy data:** Outliers and noise can significantly impact KNN's performance.

**XGBOOST**  
**Cons:**

**Black box model:** XGBoost models are less interpretable compared to SVMs, making it harder to understand their decision-making process.

**Requires more tuning:** XGBoost has numerous hyperparameters, requiring careful tuning and expertise to achieve optimal performance.

**Can be computationally expensive:** Training complex XGBoost models can be computationally demanding, especially for large datasets.