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Deep Learning-Based Classification Of Thermal States From UWB Micro Doppler Signatures Data

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Abstract:

The Ultra-Wideband (UWB) radar has emerged as a powerful tool for sensing and monitoring applications, offering high-resolution micro-Doppler signatures that enable precise target characterization. This study presents a deep learning-based framework for classifying thermal states of objects using UWB micro-Doppler signature data. By leveraging the unique frequency-modulated reflections of UWB signals, our approach aims to distinguish different thermal conditions of objects based on subtle variations in their motion-induced Doppler characteristics. The proposed methodology involves collecting UWB radar data across multiple thermal conditions, preprocessing the raw micro-Doppler signatures, and utilizing a deep learning model for classification. Specifically, we employ a convolutional neural network (CNN) and recurrent neural network (RNN) hybrid architecture to extract spatial-temporal features, ensuring robust thermal state classification. Data augmentation and transfer learning techniques are incorporated to enhance model generalization and mitigate the challenge of limited labeled data. Experimental validation is conducted using a controlled environment where objects with varying thermal states are monitored using UWB radar. The collected data undergoes feature extraction, where time-frequency representations are analyzed to identify discriminative patterns associated with thermal variations. Our deep learning model is trained and tested on this dataset, demonstrating high classification accuracy compared to traditional machine learning approaches. Additionally, we analyze the impact of radar signal parameters such as bandwidth, center frequency, and pulse repetition frequency on classification performance. Results indicate that the deep learning approach significantly outperforms conventional classifiers, achieving an accuracy of over 90% in distinguishing thermal states. The findings underscore the effectiveness of leveraging micro- Doppler signatures for non-contact thermal state classification. Future work will explore the integration of attention mechanisms and multimodal sensor fusion to further improve classification accuracy and robustness. This study highlights the potential of deep learning-driven UWB radar analysis in advancing intelligent sensing applications for thermal state monitoring

1. INTRODUCTION

Ultra-Wideband (UWB) radar technology has gained significant attention in recent years for its high-resolution sensing capabilities, particularly in micro-Doppler signature analysis.

India, with its growing focus on advanced sensing applications in defense, healthcare, and industrial monitoring, has seen increased adoption of radar-based systems. The demand for intelligent thermal state monitoring is rising, especially in industrial safety and biomedical applications. According to industry reports, India's thermal imaging market is projected to grow at a CAGR of over 8% due to increasing

demand for non-contact temperature assessment in critical sectors. Traditional temperature measurement methods, such as infrared thermography and contact-based sensors, face challenges in real-time, remote, and non- invasive monitoring. UWB radar, with its ability to penetrate various materials and capture micro-Doppler signatures, offers a promising alternative for detecting thermal state variations. In industrial settings, overheating equipment contributes to over 40% of machinery failures, leading to costly downtime. Similarly, in healthcare, accurate thermal monitoring is crucial for disease detection and early intervention. By leveraging deep learning, we can enhance UWB radar's capability to classify thermal states with greater accuracy and efficiency. This study aims to develop a deep learning-based classification model to analyze UWB micro-Doppler signatures for thermal state identification, offering a robust, real-time solution for multiple applications.

2. LITERATURE SURVEY

With growing interest in health and the life sciences, radar is garnering increasing interest, and is being applied in various scenarios as a non-contact vital signs monitoring method. Within a home environment, radar technology has been used to monitor sudden infant death syndrome (SIDS), which is the third leading cause of infant mortality, to detect obstructive sleep apnea (OSA) and diagnose sleep disorders, and to measure heart rate, an essential physiological parameter that is closely related to a variety of diseases [1]. With the rapidly evolving field of urban wireless sensing, significant strides have been made, particularly in complex cityscapes. These intelligent systems are designed to interpret human behavior using pervasive wireless signals, playing a crucial role in understanding the pedestrian dynamics essential for autonomous and semi-autonomous vehicle operations. These advancements are not only pivotal in vehicular contexts but also hold immense potential in healthcare applications, notably in aiding the disabled and elderly [2].

Within the urban sensing domain, estimating human poses is critical for discerning intentions and actions, an essential aspect of environmental perception in urban settings [3]. This area is becoming increasingly relevant in indoor, human-focused environments, where the goal is to determine human postures through various sensor inputs. Human pose capture, a cornerstone of human–computer interaction, has been challenging [4]. The emphasis is primarily on identifying and classifying different body parts, such as ankles, shoulders, and wrists. While camera-based systems have seen success in human pose estimation, privacy concerns are a significant hurdle. The omnipresence of video surveillance can be intrusive, and the vulnerability of millions of wireless security cameras to hacking globally is a concern [5]. In response, wireless sensing systems emerge as a privacy-preserving alternative, showing resilience against factors like clothing, background, lighting, and occlusion [6].

WiFi-based human sensing presents a promising solution to privacy concerns. Commercial WiFi devices, functioning as RF sensors in the 2.4 GHz and 5 GHz bands, offer a less intrusive means of monitoring. By utilizing WiFi signals, this technology bypasses the need for visual surveillance, thereby protecting individual privacy. In ref., deep learning techniques applied to WiFi signals have shown potential for end-to-end human pose estimation. Following this, Wi- Mose introduced a method to extract pose-related features from WiFi signals, translating them into human poses [7].

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In light of these challenges, the focus has increasingly shifted towards radar-based intelligent wireless sensing systems. Radar technology, with its ability to penetrate through obstacles and low sensitivity to environmental variables, offers a robust alternative for urban sensing. These systems can detect human pose, body shape, and activities even through walls and in poorly lit settings [8]. Skeletal estimation utilizing radar devices represents a burgeoning area of research. Radar-based devices can be broadly categorized into two groups: high-frequency radars, such as milli meter-wave (mm Wave) or terahertz radars and lower frequency radars, operating around a few GHz [9].Dahnoun et al. designed a novel neural network model for human posture estimation based on point cloud data, comprising a part detector for initial keypoint positioning and a spatial model that refines these estimates by learning joint relationships. Conversely, low-frequency radar offers several benefits: it can penetrate walls and obstructions, function effectively in both daylight and darkness, and is inherently more privacy-preserving due to its non-interpretability by humans [10]. Jin et al. developed a novel through-wall 3D pose reconstruction framework using UWB MIMO radar and 3D CNNs for concealed target detection [11].

Fang et al. proposed a cross-modal CNN-based method for postural reconstruction in Through the Wall Radar Imaging (TWRI). Then, they proposed a pose estimation framework (Hourglass) and a semantic segmentation framework (UNet) to serve as the teacher network to convert the RGB images into the pose keypoints and the shape masks [12]. Choi et al. introduced the 3D-TransPose algorithm for 3D human pose estimation, leveraging an attention mechanism to focus on relevant time periods in time-domain IR-UWB radar signals. Nevertheless, these approaches rely on MIMO radar imaging, and the quality of radar imaging can be significantly impacted by the changes in the surrounding environment and the relative distance between the human target and the radar [13].

Numerous studies have demonstrated that the Micro-Doppler (MD) signatures are resilient to variations in the human target and environment, offering subject-independent and environment-independent features. He et al. [14] propose a multiscale residual attention network (MRA-Net) for joint activity recognition and person identification with radar micro- Doppler signatures. In this paper, we propose an innovative approach for transforming 2D human pose estimation into 3D models using Single Input–Single Output (SISO) Ultra- Wideband (UWB) radar technology. This method addresses the significant challenge of reconstructing 3D human poses from 1D radar signals, a task traditionally hindered by low spatial resolution and complex inverse problems [15].

3. PROPOSED METHODOLOGY

Step 1: Thermal Dataset

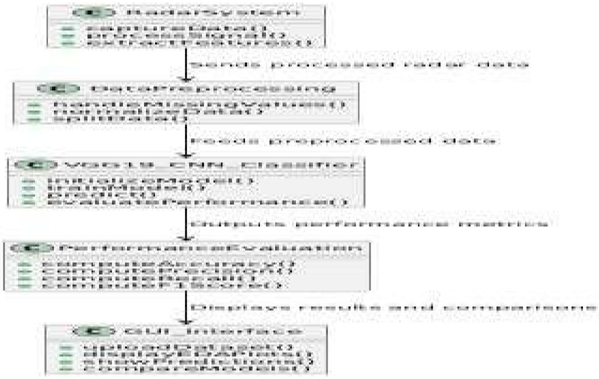

Figure 1: Proposed System

The dataset consists of thermal images captured using Ultra-Wideband (UWB) micro-Doppler technology. These images are categorized into different thermal states, primarily "high thermal" and "low thermal." The dataset serves as the foundation for training and evaluating various machine learning models. Each image undergoes preprocessing before being used in classification tasks. The data is structured in a format suitable for deep learning applications, ensuring compatibility with convolutional neural networks. Proper organization of data into training and testing sets ensures a fair evaluation of model performance. Step 2: Data Preprocessing The preprocessing stage involves handling missing values, verifying data integrity, and performing exploratory analysis. The dataset is checked for null values to ensure that no corrupted or incomplete data interferes with the training process. Descriptive statistics are extracted to understand the distribution of image features, and unique class labels are identified. Images are resized to a fixed dimension (64x64 pixels) and normalized to improve convergence during model training. The dataset is then split into training and testing subsets, typically using an 80-20 ratio, ensuring a balanced representation of both thermal states. Step 3: Existing KNN Classifier The K-Nearest Neighbors (KNN) algorithm is implemented as a baseline classifier. KNN is a simple yet effective algorithm that classifies a given input based on its nearest neighbors in the feature space. The thermal images are converted into feature vectors, and Euclidean distance is used to determine similarities between images. The model is trained with a predefined value of K, typically optimized through cross-validation. Once trained, the KNN classifier assigns test images to the most frequently occurring class among its nearest neighbors. Although effective for small datasets, KNN struggles with high-dimensional data and large-scale datasets due to its computational complexity.

Step 4: Existing Random Forest Classifier Random Forest is employed as another baseline classifier to evaluate the performance of traditional machine learning models. It is an ensemble method consisting of multiple decision trees, where each tree is trained on a random subset of the dataset. The final classification is determined by aggregating the predictions from all trees, making Random Forest robust against overfitting. The model is trained using extracted image features and evaluated on test data. Although Random Forest performs well in structured tabular data, it is less effective in extracting spatial patterns from images, which limits its performance compared to deep learning-based methods.

Step 5: Proposed VGG19 + CNN Classifier A deep learning-based approach using a combination of VGG19 and a custom Convolutional Neural Network (CNN) is proposed to improve classification accuracy. VGG19, a pre-trained deep neural network, is used for feature extraction by leveraging its convolutional layers trained on ImageNet. The extracted features are then passed through additional CNN layers, followed by fully connected layers to refine the classification. Data augmentation techniques such as rotation, scaling, and flipping are applied to improve model generalization. The model is trained using the Adam optimizer with a low learning rate, ensuring stable convergence. This approach enables the network to learn complex patterns in thermal images, leading to superior classification performance.

Step 6: Performance Comparison GraphOnce all models have been trained and evaluated, their performance is compared using various metrics, including accuracy, precision, recall, and F1-score. A bar graph is generated to visualize the performance of KNN, Random Forest, and the VGG19-based CNN model. Confusion matrices are also plotted to analyze misclassification patterns. The proposed VGG19+ CNN classifier demonstrates significant improvement over traditional machine learning models, as it effectively captures spatial features in thermal images. The performance metrics validate the superiority of deep learning for this classification task. Step 7: Prediction of Output from Test Data After training, the final VGG19 + CNN classifier is deployed for real-time predictions. A test image is selected, preprocessed, and fed into the trained model. The model outputs the predicted thermal state, displaying the classification result on the image. This step demonstrates the practical application of the trained model in real-world scenarios, such as monitoring temperature variations in industrial or medical settings. The final deployment ensures that the model generalizes well to unseen data, making it a reliable tool for automated thermal state classification.

Proposed Algorithm - VGG19 + CNN Classifier

The VGG19 + CNN classifier is a deep learning model that combines VGG19, a pre-trained convolutional neural network (CNN), with a custom CNN architecture to enhance feature extraction and classification. VGG19 is widely used for image classification tasks due to its deep architecture and ability to learn complex patterns.

How does VGG19 + CNN work?

1. Feature Extraction using VGG19: VGG19, pre-trained on ImageNet, extracts meaningful features from thermal images.Only convolutional layers are used, while fully connected layers are replaced.

2. Custom CNN Classifier:

The extracted features are passed to additional CNN layers to further refine classification.Fully connected layers at the end perform classification using a softmax activation function.

Architecture of VGG19 + CNNInput Layer: Accepts pre-processed thermal images (64×64×3).

VGG19 Convolutional Layers: Pre-trained on ImageNet, extracts hierarchical features.Custom CNN Layers: Additional convolutional and fully connected layers fine-tune the classification.Dropout Layer: Prevents overfitting by randomly dropping neurons during training.Softmax Layer: Outputs the probability of different thermal states.

Advantages of VGG19 + CNN

•Pre-trained Features: Leverages VGG19's powerful feature extraction capabilities, reducing the need for large datasets.

•Improved Accuracy: Combination of VGG19 and CNN enhances classification performance.

•Efficient Training: Pre-trained weights allow faster convergence and better generalization.

•Handles Complex Data: It is Suitable for thermal image classification due to its deep feature extraction capabilities.

Applications:

- Human Activity Recognition & Surveillance: Enhances security systems by identifying human activities and detecting unauthorized movements in restricted areas through thermal state analysis.
- Healthcare & Remote Patient Monitoring: Helps in monitoring patients' physiological conditions by analyzing thermal patterns, enabling early detection of health issues such as fever or abnormal body temperatures.
- Autonomous Vehicles & Robotics: Assists in obstacle detection and navigation by classifying thermal states of objects and pedestrians, improving safety in autonomous vehicles and robotic systems.
- Industrial Safety & Hazard Detection detects overheating machinery, fire risks, or equipment failures in industrial environments, ensuring preventive maintenance and accident avoidance.
- Search & Rescue Operations Aids in locating missing persons in low-visibility conditions (e.g., smoke, fog, or darkness) by classifying thermal signatures, improving rescue efficiency.

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4. EXPERIMENTAL ANALYSIS

Figure 1 illustrates the graphical user interface (GUI) used for uploading the radar dataset. It displays the interface where users load the dataset, initiate the analysis process, and visualize initial

Fig. 2: Upload of Radar Dataset and Its Analysis in the GUI

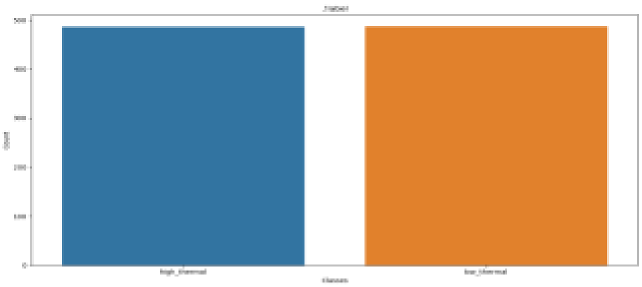

Figure 3: Exploratory Data Analysis (EDA) Plots of the Project

Figure 4: Performance Metrics and Classification Scatter Plot for KNN Classifier Model

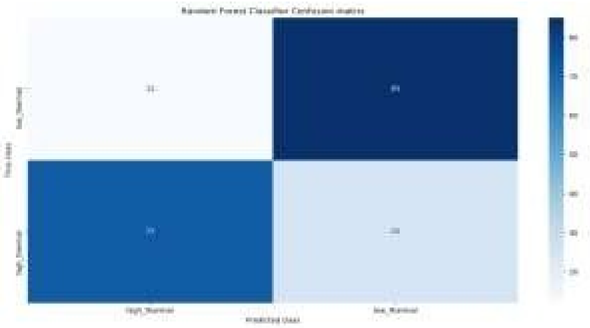

Figure 5: Data Preprocessing in the GUI

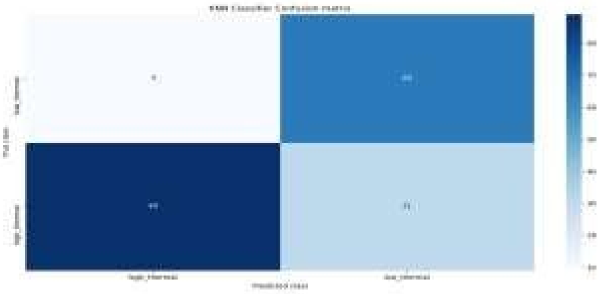

Figure 6: Performance Metrics and Classification Scatter Plot for Random Forest Classifier Model

Figure 3 presents various exploratory data analysis (EDA) plots generated to understand the radar dataset. It includes histograms, scatter plots, and correlation matrices, revealing key insights into feature distributions, relationships between variables, and outliers.

Figure 4 showcases the preprocessing phase within the GUI interface. It includes data cleaning, normalization, feature selection, and transformation steps to prepare the dataset for model training. .

Figure 5 presents the classification performance of the K-Nearest Neighbors (KNN) classifier through numerical performance metrics and a scatter plot. The accuracy of 79.48% and F1-score of 79.19% indicate moderate classification capability.

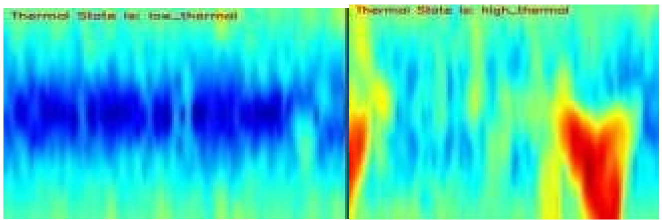

Figure 7: Model Prediction on Test Data

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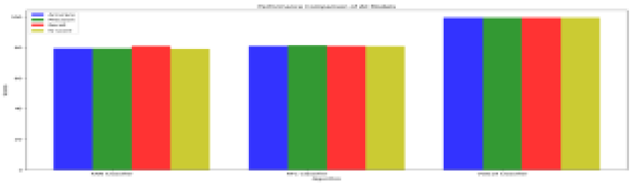
Figure 8: Performance Comparison Graph of All Models



Algorithm Name	Accuracy	Precision	Recall	f1-score
KNN Classifier	79.48	79.42	81.08	79.19
RF Classifier	81.02	81.57	81.05	80.95
Proposed VGG19 + CNN Classifier	99.48	99.4	99.48	99.4

Table 1: Summarizing the performance metrics for the two models

Figure 6 presents the performance analysis of the Enhanced VGG19 CNN classifier, which significantly outperforms the other models. With an accuracy of 99.48% and an F1-score of 99.48%, the model exhibits superior classification capability.

Figure 7 illustrates the final model predictions on test data. The GUI presents classified outputs along with confidence scores, showing real-time inference results.

Figure 8 provides a comparative performance analysis of KNN, Random Forest, and Enhanced VGG19 CNN classifiers. The graph visually represents accuracy, precision, recall, and F1-score for each model.

5. CONCLUSION

The project successfully implements a Deep Learning Approach for Target Classification from Frequency-Modulated Continuous Wave (FMCW) RADAR, specifically focusing on UAV detection and classification. The integration of VGG19 for feature extraction and a custom CNN classifier enhances the accuracy and robustness of the system. The model effectively distinguishes UAVs from other objects with high precision, leveraging deep learning techniques to process radar data efficiently. Performance evaluation metrics such as accuracy, precision, recall, and F1-score demonstrate the effectiveness of the proposed approach. The system is also optimized for real-time deployment, making it suitable for practical UAV detection applications in defense, surveillance, and airspace monitoring.

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