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Hameed, Hira; Lubna, Lubna; Ghadban, Nour; Usman, Muhammad; Arshad, Kamran; Assaleh, Khaled; Alkhayyat, Ahmed; Imran, Muhammad Ali; Abbasi, Qammer H.

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TAQWA: Teaching Adolescents Quality Wadhu/Ablution Contactlessly using Deep Learning

Hira Hameed

James Watt School of Engineering
Glasgow, UK
2683961H@student.gla.ac.uk

Lubna

Telecommunication Engineering Dept. UET
Peshawar, Pakistan
Lubnaxafi@gmail.com

Nour Ghadban

James Watt School of Engineering
Glasgow, UK
nour.ghadban@glasgow.ac.uk

Muhammad Usman

Glasgow Caledonian University
Glasgow, UK
muhammad.usman@gcu.ac.uk

Kamran Arshad

Ajman University
Ajman, UAE
k.arshad@ajman.ac.ae

Khaled Assaleh

Ajman University
Ajman, UAE
k.assaleh@ajman.ac.ae

Ahmed Alkhayyat

Department of computer technical engineering
Najaf, Iraq
ahmedalkhayyat85@iunaja.edu.iq

Muhammad Ali Imran

James Watt School of Engineering
Glasgow, UK
Muhammad.Imran@glasgow.ac.uk

Qammer H. Abbasi

James Watt School of Engineering
Glasgow, UK
qammer.abbasi@glasgow.ac.uk

Abstract—This research presents a unique and innovative approach to teaching young children the proper steps of ablution (wazoo/wudu) by utilizing a non-invasive sensing system integrated with deep learning algorithms. However, most existing ablution detection systems rely on cameras, which raise privacy concerns, face challenges with lighting conditions, and require complex training with long video sequences. We conducted experiments with a group of youngsters to evaluate the system’s effectiveness, demonstrating its potential in fostering a deeper appreciation and comprehension of religious practices among young learners. This innovative privacy-preserving ablution system employs state-of-the-art UWB-radar technology with advanced Deep Learning (DL) techniques to effectively address the challenges mentioned above. The core focus of this system is to categorize the four fundamental ablution steps: Wash Face 3x, Wash Hand 3x, Wash Head 1x, and Wash Feet 3x. By transforming the collected data into spectrograms and harnessing the sophisticated DL models VGG16 and VGG19, the proposed system accurately detects these ablution steps, achieving an impressive maximum accuracy of 97.92% across all categories with the utilization of VGG16.

Index Terms—RF sensing, micro-Doppler signatures, Hand gesture, deep learning

I. INTRODUCTION

Innovations in education and technology are constantly generating new approaches to teaching and learning that are changing the landscape of education forever. This study presents an innovative approach to teaching young children the proper techniques of ablution or wazoo/wudu by integrating non-invasive sensor technology with superior deep learning algorithms. In contrast to the typical methodologies

that heavily rely on camera-based systems, our novel solution effectively tackles many significant limitations. Using conventional ablution detection systems that rely on cameras raises problems regarding individual privacy, faces difficulties in dealing with different lighting situations, and requires complex training methods that involve extended video sequences. In order to overcome these challenges, our research proposes a non-invasive sensing technology that ensures the preservation of individuals’ privacy. By eliminating the need for cameras, we address privacy concerns and enable a discreet yet efficient method for teaching ablution steps. Moreover, this particular strategy effectively addresses the challenges associated with varying illumination conditions, a common hindrance to the precision of camera-based systems. By employing sophisticated deep learning algorithms, hence providing consistent and precise recognition of ablution steps. Existing systems struggle with typical instruction incorporating extended video sequences. In response, we streamline training to make learning more engaging and efficient. A group of young people participated in thorough trials to evaluate the system’s effectiveness. The experiments performed in our work demonstrate that the presented approach is able to help young learners understand and appreciate religious traditions.

Radar and deep learning techniques were used to recognize British Sign Language (BSL) using hand gestures in [1]. Traditional approaches were challenging; however, this non-invasive solution used radar and deep learning methods. It classified British verb and emotion signs using state-of-the-art DL models and 2-D spatiotemporal characteristics from radar

data, focused on hand gestures. The VGGNet model achieved a multiclass accuracy of up to 90.07% at 141 cm from the subject on a comprehensive BSL dataset. This study advanced hand gesture-based recognition.

[2] focuses on the instruction of wudu to students with obsessive-compulsive disorder (OCD) tendencies and offers crucial insights. Research highlights the need for vigilant identification of OCD indicators during wudu instruction, the distinction between obligatory and recommended actions, and the significance of avoiding perfectionism while addressing obsessive behaviors promptly. In addition, collaborative efforts with parents, age-appropriateness, and a detailed grasp of Islamic principles were emphasized. Instructors can create a balanced learning environment that addresses both the religious and psychological aspects of wudu practice for students with OCD tendencies by incorporating those aspects. The integration of artificial intelligence (AI) into the recognition of ablution stages has the potential to assist instructors in proactively monitoring students' wudu behavior. The use of this technology can significantly improve the teaching process by providing immediate feedback and assistance.

In [3], the authors proposed a technique to conserve water during ablution. A basic understanding of ablution processes was established in 20-to-40-year-olds. Most participants repeatedly swept water on required body areas. Wasteful behavior was discussed, and Quran-aligned water consumption was agreed upon. To save water, respondents supported an improved ablution system. The research showed that an improved ablution technique could encourage Malaysian Muslims to conduct eco-conscious ablution. [4], investigated the integration of socio-spiritual and psychotherapy approaches. Carers were observed utilizing traditional Islamic practices such as Dzikr, Wudhu, and Sholat for stability, and relaxation techniques during anxious moments. Ablution played a crucial role, with a particular emphasis on sensory aspects and procedural procedures. Mental stability was evident in the children's daily functioning and minimal self-help during anxiety. [5], showed Muslims utilized six to nine liters for ablution despite needing only two. A novel device was proposed to conserve water during ablution. A crane with a camera and servo motor regulated water flow based on identifying the object beneath. It adjusted water needs for different ablution stages. This adaptive system can promote water conservation and environmental responsibility beyond ablution. In [6], tracked Muslim prayer movements and cycle counts. The authors employed image processing and a webcam to track missed cycle counts, overcoming sensor-equipped prayer mats. The proposed method used posture detection to match captured movements with datasets, achieving successful trials.

In this article, the proposed innovative ablution system prioritizes privacy and uses cutting-edge Ultra-Wideband (UWB) radar technology and Deep Learning (DL) approaches to solve the problems listed above. It focuses on categorizing the four key ablution steps: Wash Hand 3x, Wash Face 3x, Wash Head 1x, and Wash Feet 3x. This rigorous categorization underpins step identification. By converting the data into spectrograms

and using DL models like VGG16 and VGG19, the results show outstanding proficiency in precisely detecting these subtle ablution steps. We achieved an impressive maximum accuracy rate of 97.00% across all categories demonstrating the robust performance of our proposed method and its potential to improve both practice instruction and understanding.

The aim of this article is to provide a thorough evaluation of the non-invasive sensing system's potential for teaching young children the steps of ablution, thereby encouraging a deeper appreciation for religious practices and rituals. The remaining sections of this paper are organized as follows: Section II examines the methodology used for this research. It analyzes the complexities of collecting relevant gestures, the experimental setup, data collection methods, and the implementation of a deep learning framework. In Section III, the analysis of the ablution system is presented, highlighting the precise identification of every step, and the empirical results are shared highlighting achievements. Section IV concludes the article with a summary of the findings, an analysis of its implications, and suggestions for future research.

II. METHODOLOGY

A. The Complexity of Hand Gesture

In order to process the visual data acquired by cameras or sensors, hand gesture recognition uses advanced algorithms and machine learning approaches [7]. Future advancements in the field of hand gesture recognition show great promise for using our natural gestures as a universal language that computers can easily understand and respond to. This exciting area of research and development is shaping a more connected and interactive technological landscape. We are building a future where the human-computer connection is fluid, intuitive, and revolutionary by utilizing the power of hand gestures. This revolutionary technology has the potential to revolutionize various industries, from gaming and virtual reality to healthcare and industrial automation [8]. Hand gesture recognition has the potential to be a powerful tool for human-computer interaction. However, a number of difficulties need to be rectified in order for it to reach its full potential. These difficulties include algorithm robustness, accuracy, and privacy issues [9]. One of the main challenges in hand gesture recognition is the diversity of gestures. The human hand is very flexible and can make many different static and dynamic gestures, making it difficult to recognize some similar gestures and putting forward higher recognition requirements [10].

B. Experimental setup and data collection

A UWB radar sensor (Xethru X4M03) developed by Novelda is used in this research to introduce a method for identifying ablution steps. Antennas and a transmitter are combined in the radar unit to provide accurate distance measurements and record small motion details. As shown in Fig. 2(a), the radar was placed one meter away from the subject or target during data collection. Each ablution step, as depicted in Fig. 1(a), was carried out within 15 seconds. During this time, RF signals were transmitted and received within the specified range for

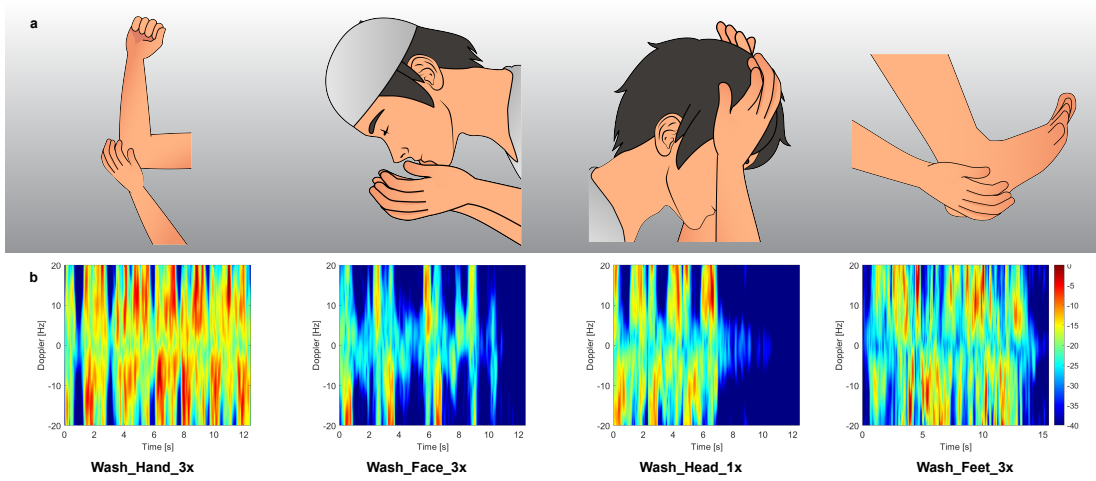


Fig. 1: (a) Gesture of four mandatory ablation steps. (b) The obtained sample of spectrogram.

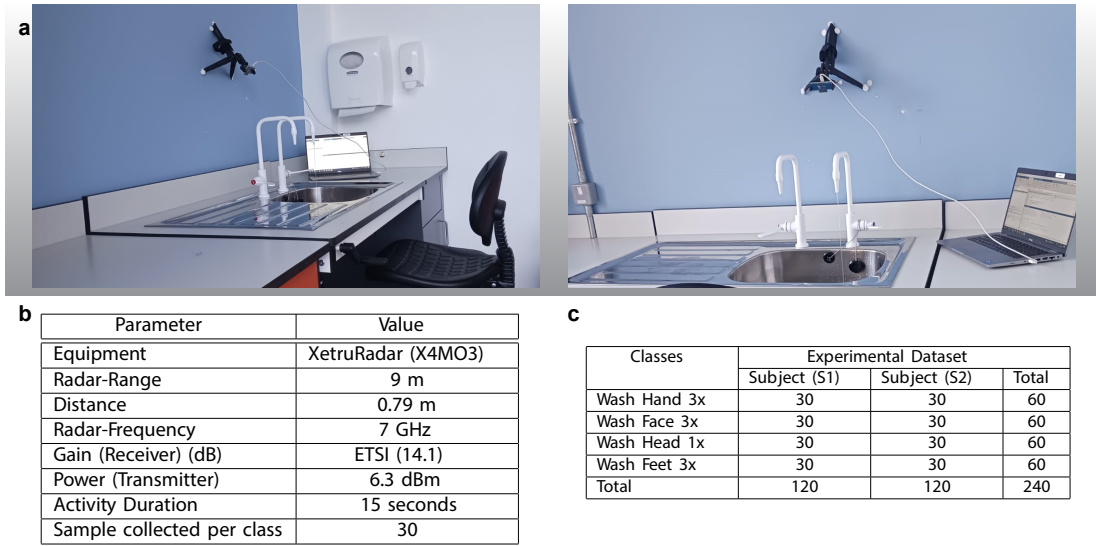


Fig. 2: The overall System parameter and visualization. (a) The experimental setup. (b) The parameter setting of the proposed system. (c) A summary of the gathered data, the count of participants involved, and the conducted activities.

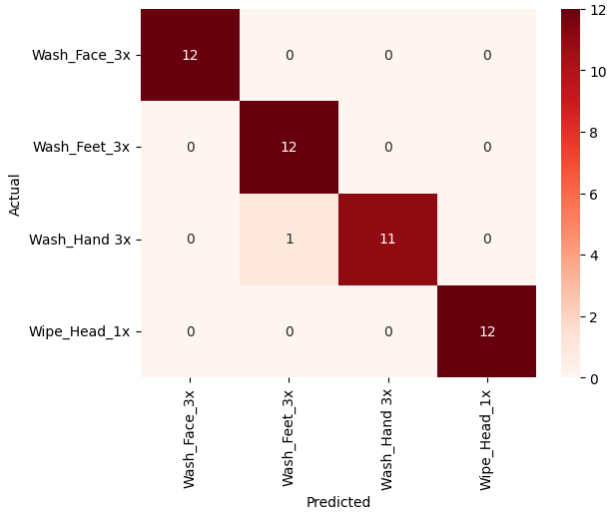
each activity. The gathered data was subsequently recorded in ".dat" file and then convert into a spectrogram using signal processing steps, with the x-axis denoting time and the y-axis representing Doppler frequency (Hz), as depicted in Fig. 1(b). Spectrograms offer insights into the dynamic ablation movements. To ensure a sufficient quantity of data samples, participants were directed to perform each ablation step multiple times. Two female volunteers were involved in the data collection procedure. Four unique ablation step categories—Wash Hand 3x, Wash Face 3x, Wash Head 1x, and Wash Feet 3x—were carefully collected, a total of 240 data samples. The distribution of the ablation steps dataset is presented in Fig. 2.(c) In each experiment, 120 data samples were collected from each participant, with 30 samples per class. Among the combined dataset, 192 were used for training

and 48 for testing. Further details about the experimental setup and system parameters can be found in Fig. 2(b).

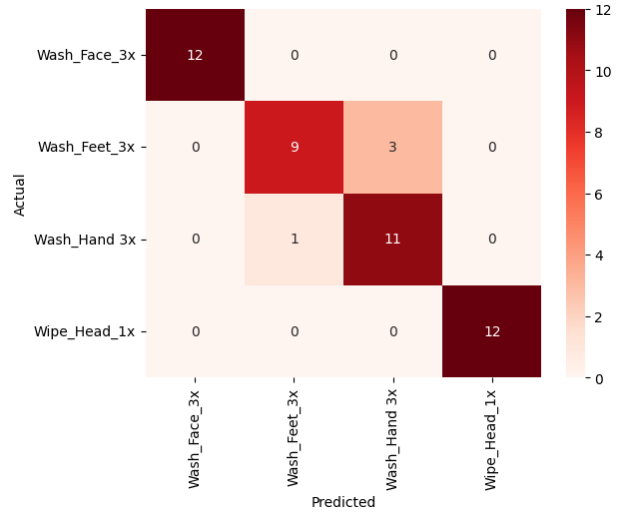
C. Deep Learning Architecture

The spectrograms generated in the previous step are fed into deep-learning models for classification. Two distinct pre-trained models, namely VGG16 and VGG19, were used for this purpose. These models were employed to classify the collected data into the four specified classes: Wash Hand 3x, Wash Face 3x, Wash Head 1x, and Wash Feet 3x.

The VGG16 architecture consists of 16 convolutional layers using the rectified linear unit (ReLU) activation function. Each convolutional layer has a kernel size of 3x3, followed by a 2x2 max-pooling layer. The convolution layers serve as weight retainers and automatic feature extractors. The classifier consists of three fully connected layers (FC). These convolution



(a) VGG16



(b) VGG19

Fig. 3: The confusion matrix of deep learning models (a) VGG16. (b) VGG19.

and FC layers store training weights and parameters for result calculation.

The VGG19 architecture is composed of 19 layers and employs a 3x3 filter to capture image details. It incorporates five stages of convolutional layers, five pooling layers, and three fully connected layers. The depth of the convolutional kernel has been increased from 64 to 512 in the VGG19 network, enhancing the extraction of image feature vectors. Each stage of convolutional layers is followed by a pooling layer with a size and step size of 2x2.

III. SYSTEM EVALUATION AND RESULTS

A. Criteria for Evaluation

In this case, evaluating the effectiveness of the VGG16 and VGG19 deep learning models in correctly categorizing four different processing stages is the main emphasis. The accuracy of the model's predictions for the appropriate ablation classes is measured using the average test accuracy, which is determined by Equation (4). Additionally, by combining precision and recall while taking true positives, false positives, and false negatives into account, the F1 Score, which is calculated using Equations (3) and (1), offers a thorough accuracy metric.

$$Precision = \frac{\sum TP}{\sum TP + \sum FN} \quad (1)$$

$$Recall = \frac{\sum TP}{\sum TP + \sum FN} \quad (2)$$

$$F1 - Score = 2 \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

$$Accuracy = \frac{\sum (TP + TN)}{\sum (TP + FP + TN + FN)} \quad (4)$$

Models	Accuracy (%)	Precision	Recall	F1-Score
VGG16	97.92	0.98	0.98	0.98
VGG19	91.67	0.92	0.92	0.92

TABLE I: Metrics such as accuracy, recall, precision, and F1-score were compared between both VGG16 and VGG19 models.

B. Results and discussions

The data sets, which included four main ablation steps Wash Hand 3x, Wash Face 3x, Wash Head 1x, and Wash Feet 3x were collected from two people of different age groups. The data split for the experiments was 80% training and 20% testing. Both the VGG16 and VGG19 pre-trained models were trained for 50 epochs using the Adamax optimizer with a learning rate of 0.001.

The experimental results are illustrated in Fig. 3. Fig. 3(a) shows the confusion matrix used by the VGG16 model to ablation class classification using combined datasets. The figure shows that most classes are correctly identified, while Wash Hand 3x has a classification accuracy of 90%, with a 10% resemblance to Wash Feet 3x.

Likewise, the confusion matrix for the combined dataset utilizing VGG19 is depicted in Fig. 3(b). The majority of classes are accurately classified, though Wash Hand 3x and Wash Feet 3x display discrepancies. Wash Feet 3x is similar to Wash Hand 3x by 25%, and Wash Hand 3x bears an 8% similarity to Wash Feet 3x.

The complete accuracy, precision, recall, and F1-score results for the evaluated DL models are shown in Table. I. The table clearly shows that, on the combined dataset VGG16 outperforms VGG19, achieving an outstanding overall test accuracy of 97.92%.

IV. CONCLUSION AND FUTURE WORK

Our study provides a novel method for teaching young children about ablution procedures using non-invasive sensor technology and deep learning models. This approach enhances learning by providing practical guidance in real-time. Our tests have shown that the system can classify ablution processes as Wash Hand 3x, Wash Face 3x, Wash Head 1x, and Wash Feet 3x. In order to train the VGG16 and VGG19 deep learning models, we used micro-Doppler spectrograms, and we were able to achieve approximately 100% accuracy for the majority of classes using combined datasets. In the future, adding more diverse data from various people and situations could make the system even better at adapting and working effectively.

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