IEEE
CIVEMSA 2022
IEEE International Conference on Computational Intelligence & Virtual Environments for Measurement Systems and Applications

June 15-17, 2022 – Chemnitz, Germany

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Welcome Message from the Chairpersons

Dear Friends and Colleagues,

As General Chairs of the 10th IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA 2022), we welcome you to Chemnitz, Germany. IEEE CIVEMSA 2022 is an international conference dedicated to computational intelligence, virtual environments, and human-computer interaction technologies for measurement systems and related applications. This year, the conference will be held in a hybrid form and it is hosted by The Chair of Measurement and Sensor Technology at Chemnitz University of Technology. We are proud to have been given the opportunity to lead an enthusiastic group of worldwide experts who participated in the creation of the program in front of you. Our sincere thanks go to the HONORARY CO-CHAIRS, Emil M. Petriu and Vincenzo Piuri and Program CO-CHAIRS, Octavian Postolache, Ulrike Thomas, and Georg Jahn. We would also like to express our gratitude to all the other members of the organizing committee, including local arrangements chairs. The program committee members have provided high-quality reviews, allowing the conference to maintain its high-quality standards. Last, but not least, our student volunteers are making us all feel welcome. Job well done!

The official sponsors of CIVEMSA 2022 are IEEE Computational Intelligence Society (CIS), IEEE Instrumentation and Measurement Society, CRC 1410 Hybrid societies, and Chemnitz School of Metrology (CSM e.V.). Their support is critical to our ability to continue our work. Without the generosity of donors like you, we wouldn't be able to succeed. Finally, we'd want to express our gratitude to our employers for their willingness and approval in establishing work settings that support our professional service. You are invited to contact us if you have any questions or comments about the conference's organization or program. We hope you will remember CIVEMSA 2022 as a wonderful professional and personal experience. It has certainly been so for us.

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HYBRID SOCIETIES

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Keynote Speakers

INÈS CHIHI - UNIVERSITY OF LUXEMBOURG

Title: Artificial intelligence is really the best solution for systems with unpredictable behavior? A comparative study between ANN and Multi-model approach

Abstract

Artificial intelligence and Data-driven models are well suggested for modeling complex and non-linear processes. However, they require a very large computation time for data preparation, analysis, and and learning. Indeed, complex problems require an extended network that can have exceptionally long and tedious computations, especially at inference instants.

To overcome these problems, we propose a hybrid technique based on multi-model structure. This structure is suggested for modeling nonlinear process by decomposing its nonlinear operating domain into a defined number of sub-models, each one representing a well-defined operating point.

Thus, the multi-model concept is considered an interesting method to improve the performance of the model in terms of accuracy and without increasing too much of the complexity of the empirical model, the training time or the number of parameters to be estimated.

As an example, we present a comparative study between Artificial Neural Network (ANN), known as the most used and efficient technique in empirical modeling, and the proposed multimode approach. This comparative study will be applied to estimate the muscle forces of the forearm from the muscle's activities.

Speaker's Bio

Dr. Inès CHIHI was born in Tunis, Tunisia in 1984. She obtained her PhD degree in electrical engineering from the National Engineering School of Tunis in 2013. From the same school, she obtained her "Habilitation Universitaire" degree in electrical engineering in 2019.

Inès was a professor at the Higher Institute of Applied Sciences and Technologies of Gafsa Tunisia, from 2013 until 2016. Then she joined the National Engineering School of Bizerta, Tunisia (2016-2022).

Since 2017, Inès is also the founder and president of the Association of Energy Efficiency and the Environment (AEEE) and she is a member of the first Tunisian Network for Energy Transition. Inès is a member of the Organization for Women in Science for the Developing World (OWSD), Program Unit of UNESCO.

Since January 14, 2022, Inès has joined the Department of Engineering (DoE) at the University of Luxembourg. Her research area is based on smart sensors for estimation and identification for complex systems with unpredictable behaviors. She applies her approaches in various fields: bioengineering, energy, industry 4.0, etc.

PASQUALE ARPAIA - UNIVERSITY OF NAPOLI FEDERICO II (ITALY)

Title: Wearable Brain-Computer Interfaces for measuring mental states: After data, are we loosing also thoughts privacy?

Abstract

In the last two decades, Brain-Computer Interface (BCI) has gained great interest in the technical-scientific community, andmore and .more effort has been done to overcome its limitations in daily use. In Industry 4.0 framework, the human becomes part of a highly composite automated system and new-generation user interfaces, integrating cognitive, sensorial, and motor skills, are designed. Humans can send messages or decisions to the automation system through BCI by intentional modulation of brain waves. However, through the same signal, the system (and, hence, also the human being part of it) acquires information on the user status.

In this talk, the most interesting results of this technological research effort, as well as its further most recent developments, are reviewed. In particular, after a short survey on research at the University of Naples Federico II also in cooperation with CERN, the presentation focuses mainly on state-of-the-art research on wearable measurement systems for acting robots and monitoring mental states (emotions, engagement, distraction, stress and so on). Tens of disparate case studies, carried out by Federico II researchers, spacing from children autism rehabilitation to robotic inspection in hazardous sites, are reported. Special attention is given also to ethic and law issues arising from daily use, by leaving puzzling questions to attendees..

Speaker's Bio

Dr. Pasquale Arpaia received his Master's Degree and Ph.D. in Electrical Engineering at the University of Napoli Federico II (Italy), where he is a full-time professor of Instrumentation and Measurements. He is Director of the Interdepartmental Center for Research on Management and Innovation of Health (CIRMIS), Head of the Instrumentation and Measurement for Particle Accelerators Laboratory (IMPALab), the Augmented Reality for Health Monitoring Laboratory (ARHeMlab), the Hi-Tech Academic FabLab Unina, as well as Chairman of the Stage Project of the University Federico II. He is Team Leader at European Organization for Nuclear Research (CERN). He was also a professor at the University of Sannio, an associate at the Institutes of Engines and Biomedical Engineering of CNR, and now of INFN Section of Naples.

He is Associate Editor of the Institute of Physics Journal of Instrumentation, Elsevier Journal Computer Standards & Interfaces, MDPI Instruments, and in the past also of IEEE Transactions on Electronics Packaging and Manufacturing. He was Editor at Momentum Press of the Book Collection "Emerging Technologies in Measurements, Instrumentation, and Sensors". Recently, he was scientific responsible for more than 30 awarded research projects in cooperation with industry, with related patents and international licenses, and funded 4 academic spin-off companies. He acted as scientific evaluator in several international research call panels. He continuously serves as organizing and scientific committee member in IEEE and IMEKO Conferences. He is a plenary speaker in several scientific conferences.

He published 3 books, several book chapters, and about 300 scientific papers in journals and national and international conference proceedings. His PhD students received awards in 2006, 2010, and 2020 at IEEE I2MTC, in 2016 at IMEKO TC-10, and in 2012 and 2018 at World Conferences.

JOSEF F. KREMS - CHEMNITZ UNIVERSITY OF TECHNOLOGY

Title: Drive me home please! Contributions from Human Factors to Vehicle Automation

Abstract

Prototypes of highly automated cars are already being tested on public roads in Europe, Japan and the United States. Automated driving promises several benefits such as improved safety, reduced congestions and emissions, higher comfort as well as economic competitiveness and enhanced mobility in the context of demographic changes. These benefits are often claimed on the basis of a technology-centered perspective of vehicle automation, emphasizing technical advances. However, to exploit the potential of vehicle automation, human-machine-related issues are considered a key question, shifting the perspective towards a human-centered view on automation.

Research on human-automation interaction pointed out already “ironies of automation” that can undermine the expected benefits. Relevant issues mainly relate to the role change in various levels of automation, i.e. mode awareness and transitions from manual to automated control, reduced vigilance due to the monotony of supervising tasks in partially automated driving, changes in attention allocation and engagement in non-driving tasks, out-of-the-loop unfamiliarity resulting in reduced situation awareness, mental models of automation, trust calibration as well as misuse and overreliance. For reducing negative automation effects and enabling successful human-automation interaction, feedback on automation states and behaviors is considered a key factor.

In this talk, I will describe new challenges that arise from the technological development for human factors and how human factors can contribute to a “hybrid architecture”. The focus will be on our own research results on take-over-requests, communication between highly automated cars and other road users, and on comfort and acceptance. part of a highly composite automated system and new-generation user interfaces, integrating cognitive, sensorial, and motor skills, are designed. Humans can send messages or decisions to the automation system through BCI by intentional modulation of brain waves.

Speaker’s Bio

Josef F. Krems, Professor of Cognitive and Engineering Psychology, graduated at the University of Regensburg in 1980. He then joined the group for Cognitive Psychology as a research assistant and did a PhD in Psychology (1984). For his habilitation (second PhD) he worked on Computer modeling and expert systems (1990). From 1991-1993 he was a Visiting Assistant Professor at Ohio State University, Columbus (OH), where he worked on computational models of diagnostic reasoning. Then he became a Visiting Assistant Professor at the Centre for Studies on Cognitive Complexity at the University of Potsdam (1994-1995). Since 1995 he is a full professor at Chemnitz University of Technology. In 2006 he was invited as Visiting Professor to Chung-Keng University, Taiwan. His current research projects are on Electro-mobility, Man-Machine Interaction, Advanced Driver Assistant systems and highly automated driving.

Program Schedule

Wednesday, June 15, 2022

8:30 - 9:00	**Opening**
9:00 - 10:40	**IOT**
10:40 - 11:00	**Coffee Break**
11:00 - 11:45	**Keynote 1: Dr. Pasquale Arpaia**
11:45 - 13:00	**Multi Sensors and Data Fusion**
13:00 - 14:00	**Lunch**
14:00 - 15:40	**Hybrid Societies I: Augmented & Virtual Reality**
15:40 - 16:00	**Coffee Break**
16:00 - 18:00	**Hybrid Societies II: Humans interacting with embodied technologies**
18:30	**Conference Banquet Dinner**

Thursday, June 16, 2022

9:00 - 9:45	**Keynote: Dr. Inès Chihi**
9:45 - 10:40	**Medical Image Processing**
10:40 - 11:00	**Coffee Break**
11:00 - 13:00	**Signal Processing, Test and Prediction**
13:00 - 14:00	**Lunch Break**

14:00 - 15:40	**Hybrid Societies III: Automated Vehicles and Drones**
15:40 - 16:00	**Coffee Break**
16:00 - 18:00	**Special Session 2: Methods, Tools and Systems and their Application for Telemanipulation**

Friday, June 17, 2022

9:00 - 9:45	**Keynote:Josef F. Krems**
9:45 - 10:40	**Image Processing**
10:40 - 11:00	**Coffee Break**
11:00 - 12:40	**Special Session 3: Body attached wireless sensor network**
12:40 - 14:00	**Conference Reception**
14:00 - 16:00	**Machine Learning**
16:00	**Closure**

Wednesday, June 15

09:00 - 10:40 (Europe/Berlin)
IOT
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

9:00
Performance Evaluation of LoRa in Mixed Environments of sparsely Distributed Vegetation and Urban scenarios
Kaushal Kishore Tiwari (IIIT Sri City, India); Raja VaraPrasad (Indian Institute of Information Technology (IIIT) Sricity, India); Hrishikesh Venkataraman (Indian Institute of Information Technology (IIIT) & Center for Smart Cities, India)

9:20
Senseful Sensors: Learnings and Optimizations for IoT Sensors in HCI Research
Albrecht Kurze (TU Chemnitz, Germany)

9:40
Benchmarking a Sensor-less Kinetic Transducer for Inertial Measurement Unit for Industrial IoT Applications
Dhouha El Houssaini (University of Technology, Germany & National School of Engineers of Sfax, Tunisia); Carlo Trigona (University of Catania, Italy); Abdallah Adawy (Technische Universität Chemnitz, Germany & Jordan University of Science and Technology, Jordan); Kholoud Hamza (National School of Electronics and Telecommunications of Sfax., Tunisia); Roberto La Rosa (STMicroelectronics, Italy); Salvatore Baglio (University of Catania, Italy); Olfa Kanoun (Chemnitz University of Technology, Germany)

10:00
Efficiency of Spectral Subtraction Algorithms for an Urban Audio Acquisition System Using IoT Devices
Evan Fallis, Petros Spachos and Stefano Gregori (University of Guelph, Canada)

10:20
Energy-Efficient Short-Long Range Communication Network Combining LoRa and Low-Power Radio for Large-Scale IoT Applications
Sabrine Khriji (Technische Universität Chemnitz, Germany & National School of Engineers of Sfax, Tunisia); Dhouha El Houssaini (University of Technology, Germany & National School of Engineers of Sfax, Tunisia); Olfa Kanoun (Chemnitz University of Technology, Germany)

11:00 - 11:45 (Europe/Berlin)
Keynote 1
Chair: Abdulmotaleb El Saddik (University of Ottawa, Canada)

Data Processing and Information Retrieval of Atmospheric Measurements
Dr. Pasquale Arpaia (University 0f Napoli Federico II, Italy)

11:45 - 13:00 (Europe/Berlin)
Multi Sensors and Data Fusion
Chair: Abdulmotaleb El Saddik (University of Ottawa, Canada)

11:45
Data Processing and Information Retrieval of Atmospheric Measurements
Dali Wang (Christopher Newport University, USA); Ying Bai (Johnson C. Smith University, USA)

12:05
Development and Application of Outdoor Router Cost Estimation with Parametric Modelling Technique
Abel Chai Yu hao (Swinburne University of Technology Sarawak Campus, Malaysia); Yi Lung Then (Swinburne University of Technology, Malaysia); Fei Siang Tay (Swinburne University of Technology Sarawak Campus, Malaysia)

12:25
Gas Discrimination Analysis of Neural Network Algorithms for a Graphene-Based Electronic Nose
Sebastian Anton Schober (Infineon Technologies AG Neubiberg & Institute for Integrated Circuits, Johannes Kepler University Linz, Germany); Cecilia Carbonelli (Infineon Technologies AG, Germany); Robert Wille (Technical University of Munich, Germany)

12:45
Multi-Sensor-based Method for Multiple Hard Faults Identification in Complex Wired Networks
Dhia Haddad (Professorship Measurement and Sensor Technology, Chemnitz University of Technology, Chemnitz, Germany & University of Sousse, Tunisia); Lidu Wang (Professorship Measurement and Sensor Technology, TU Chemnitz, Germany); Ahmed Yahia Kallel (TU Chemnitz, Germany); Najoua Essoukri Ben Amara (University of Sousse & Laboratory of Advanced Technology and Intelligent Systems, Tunisia); Olfa Kanoun (Chemnitz University of Technology, Germany)

14:00 - 15:40 (Europe/Berlin)
Hybrid Societies I: Augmented & Virtual Reality
Chair: Georg Jahn (TU Chemnitz, Germany)

14:00
Investigation on Tactile Perception of Ultrasonic Haptics Devices
Christian Fuchs, Christian Kollatsch, Leon Gärtner, Adelina Heinz, Alexander von Kiesling, Susanne Weinhold and Franziska Klimant (University of Technology Chemnitz, Germany)

14:20
A hybrid control strategy for capturing cognitive processes in virtual reality (VR) in a natural and efficient way
Sascha Feder, Alexandra Bendixen and Wolfgang Einhäuser (Chemnitz University of Technology, Germany)

14:40
Interactable Topographical Map with Remote Cross Reality Collaboration Support
Jacob D Chesnut (University of Washington Bothell, USA); Kelvin Sung (University of Washington, Bothell, USA)

15:00
An Immersive Approach for Scholar Profile Visualization
Diana Purwitasari, Fariz Adhiyasa, Nanik Suciati and Hadziq Fabroyir (Institut Teknologi Sepuluh Nopember, Indonesia); Surya Sumpeno (Institute Teknologi Sepuluh Nopember, Indonesia); Mauridhi Hery Purnomo (Institut of Technology Sepuluh Nopember, Indonesia)

16:00 - 18:00 (Europe/Berlin)
Hybrid Societies II: Humans interacting with embodied technologies
Chair: Georg Jahn (TU Chemnitz, Germany)

16:00
Multiview Representation Learning for Human Activity Recognition
Lukmon Rasaq (University of North Carolina Wilmington, USA); Massinissa Hamidi (University Sorbonne Paris Nord Villetaneuse, France); Gulustan Dogan (University of North Carolina Wilmington, USA); Aomar Osmani (University Sorbonne Paris Nord Villetaneuse, France); Nouran Alotaibi (University of North Carolina Wilmington, USA)

16:20
Comparison of Machine Learning and Rule-based Approaches for an Optical Fall Detection System
Tobias Rothmeier and Stefan Kunze (Deggendorf Institute of Technology, Germany)

16:40
An Interactive Dashboard to Support Policymaking of Reopening School on Covid-19 Pandemic
Feby Artwodini Muqtadiroh and Diana Purwitasari (Institut Teknologi Sepuluh Nopember, Indonesia); Muhammad Reza Pahlawan (Institut Teknologi Sepuluh Nopember Surabaya, Indonesia); Eko Mulyanto Yuniarno (Institut Teknologi Sepuluh November, Indonesia); Supeno Mardi Susiki Nugroho (Sepuluh Nopember Institute Of Technology, Indonesia); Mauridhi Hery Purnomo (Institut of Technology Sepuluh Nopember, Indonesia)

17:00
Positive User Experience: Novices Can Assess Psychological Needs
Vera Fink (Mittweida University of Applied Sciences, Germany)

17:20
Warm Liquid Spill Detection and Tracking Using Thermal Imaging
Ghazal Rouhafzay, Haitao Tian and Pierre Payeur (University of Ottawa, Canada)

Thursday, June 16

08:30 - 09:00 (Europe/Berlin)
Opening
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

09:00 - 09:45 (Europe/Berlin)
Keynote 2
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

Artificial intelligence is really the best solution for systems with unpredictable behavior? A comparative study between ANN and Multi-model approach
Dr. Inès Chihi (University of Luxembourg)

09:45 - 10:40 (Europe/Berlin)
Medical Image Processing
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

9:45
ALLNet: Acute Lymphoblastic Leukemia Detection Using Lightweight Convolutional Networks
Angelo Genovese (Università degli Studi di Milano, Italy)

10:05
Covid-19 Lung Segmentation using U-Net CNN based on Computed Tomography Image
Fx Ferdinandus (Institut Teknologi Sepuluh Nopember Surabaya & Institut Sains dan Teknologi Terpadu Surabaya, Indonesia); Eko Mulyanto Yuniarno (Institut Teknologi Sepuluh November, Indonesia); I Ketut Pumama (Institut Teknologi Sepuluh Nopember, Indonesia); Mauridhi Hery Purnomo (Institut of Technology Sepuluh Nopember, Indonesia)

10:25
Biliary Atresia Detection Using Color Clustering and Nearest Neighbor Classification: A User Interactive Approach
Angelo Genovese (Università degli Studi di Milano, Italy); Xhuliano Bushi (Weedea Communication & Coding Lab, Italy); Lorenzo D'Antiga (Azienda Socio Sanitaria Territoriale Papa Giovanni XXIII, Italy); Milena Lazzaroni (Amici della Pediatria, Italy); Gabriele Mawi (Weedea Communication & Coding Lab, Italy); Emanuele Nicastro (Azienda Socio Sanitaria Territoriale Papa Giovanni XXIII, Italy); Vincenzo Piuri (Università degli Studi di Milano, Italy); Andrea Scocciolini (Weedea Communication & Coding Lab, Italy); Fabio Scotti (Universita' degli Studi di Milano, Italy); Andrea Tomarelli and Tommaso Vicarelli (Weedea Communication & Coding Lab, Italy)

11:00 - 13:00 (Europe/Berlin)
Signal Processing, Test and Prediction
Chair: Pasquale Arpaia (University 0f Napoli Federico II, Italy)

11:00
Mixed-Signal ADC Tester for Education in Instrumentation and Measurement Technology
Serge Demidenko (Sunway University, Malaysia); Moi Tin Chew and Joshua Xu (Massey University, New Zealand)

11:20
Soft Homotopy through Moore-Penrose Inverse
Bamrung Tau Siesakul (Srinakharinwirot University, Thailand)

11:40
Identification of Specific Human Behaviours from Cortisol profiles using Bagged and Boosted Decision Trees
Ankita Mohapatra (California State University Fullerton, USA); Timothy Trinh (California State University Fullerton, USA); Stevan Pecic (California State University Fullerton, USA); Pulin Agrawal (Independent Artificial General Intelligence Researcher, USA)

12:00
Automated Generation, Execution, and Evaluation of Virtual Test Series
Tobias Osterloh (RWTH Aachen University & Institute for Man-Machine Interaction, Germany); Ulrich Dahmen and Jürgen Roßmann (RWTH Aachen University, Germany)

12:20
Trade-off between Spectral Feature Extractors for Machine Health Prognostics on Microcontrollers
Umut Onus (IMMS Institut fuer Mikroelektronik - und Mechatronik-Systeme GmbH, Germany); Sebastian Uziel (Institute of Microelectronic and Mechatronic Systems, Germany); Tino Hutschenreuther (IMMS, Germany); Silvia Krug (Mid Sweden University, Sweden)

14:00 - 15:40 (Europe/Berlin)
Hybrid Societies III: Automated Vehicles and Drones
Chair: Ulrike Thomas (Chemnitz University of Technology, Germany)

14:00
Design of On-body Tactile Displays to Enhance Situation Awareness in Automated Vehicles
Francesco Chiossi, Steeven Villa, Melanie Hauser and Robin Welsch (LMU Munich); Lewis L. Chuang (Humans and Technology, Institute for Media Research, Faculty of Humanities, Chemnitz University of Technology)

14:20
Manually or Autonomously Operated Drones: Impact on Sensor Data towards Machine Learning
Rialda Spahic and Mary Ann Lundteigen (Norwegian University of Science and Technology, Norway)

14:40
Use of an automated guided vehicle as a telepresence system with measurement support
Sven Winkler, Sebastian Knopp, Nick Weidensager, Jennifer Brade, Georg Jahn and Philipp Klimant (TU Chemnitz, Germany)

15:00
Should I wait or should I go? - Deciphering Implicit Communication Cues for Cooperative Interactions in Left-Turn Scenarios
Ann-Christin Hensch, Matthias Beggiato and Josef Krems (Chemnitz University of Technology, Germany)

15:20
Analysis of eye gaze given different automated driving styles in an urban environment
Konstantin Felbel, André Dettmann and Angelika C. Bullinger (Chemnitz University of Technology, Germany)

16:00 - 18:00 (Europe/Berlin)
Robotic
Chair: Ulrike Thomas (Chemnitz University of Technology, Germany)

16:00
A GA-Based Learning Strategy Applied to YOLOv5 for Human Object Detection in UAV Surveillance System
Aprinaldi Bin Jasa Mantau (Graduate School of Computer Science and System Engineering, Kyushu Institute of Technology, Japan)

16:20
3D Text Recognition and Localization From Point Clouds via 2D Projection and Virtual Camera
Adrian Mai and Chelsea M Mediavilla (NIWC Pacific, USA); Jane N Berk (Naval Information Warfare Center, USA); Mark Bilinski (NIWC Pacific, USA); Raymond Provost (Naval Information Warfare Center, USA)

16:40
ANNarchy - iCub: An Interface for Easy Interaction between Neural Network Models and the iCub Robot
Torsten Fietzek, Helge Ülo Dinkelbach and Fred Hamker (Chemnitz University of Technology, Germany)

17:00
Detecting Landmark Misrecognition in Pose-Graph SLAM via Minimum Cost Multicuts
Kazushi Aiba, Kanji Tanaka and Ryogo Yamamoto (University of Fukui, Japan)

17:20
Model Study for Outdoor Data Transmission Performance
Abel Chai Yu hao (Swinburne University of Technology Sarawak Campus, Malaysia); Yi Lung Then (Swinburne University of Technology, Malaysia); Fei Siang Tay (Swinburne University of Technology Sarawak Campus, Malaysia)

17:40
Gesture Based Symbiotic Robot Programming for Agile Production
Carl Gäbert (Chemnitz University of Technology, Germany); Achraf Djemal and Hiba Hellara (National School of Electronics and Telecommunications of Sfax, Tunisia); Bilel Atitallah (Technische Universität Chemnitz & National Engineering School of Sfax, Germany); Rajarajan Ramalingame (Technische Universität Chemnitz, Germany); Rim Barioul (Technische Universitat Chemnitz, Germany & CEM Research Laboratory at the National School of Engineer of Sfax, Tunisia); Dennis Salzseiler, Ellen Fricke, Olfa Kanoun and Ulrike Thomas (Chemnitz University of Technology, Germany)

Friday, June 17

09:00 - 09:45 (Europe/Berlin)
Keynote 3
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

Drive me home please! Contributions from Human Factors to Vehicle Automation
Josef F. Krems (Chemnitz University of Technology, Germany)

09:45 - 10:40 (Europe/Berlin)
Image Processing
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

9:45
A Deep Learning Approach for Hyperspectral Image Classification Augmented with Additive Noise for More Stable Prediction in Remote Sensing and Aerospace Surveillance
Vusal Pasha (Umass Lowell, USA); Dalila B. Megherbi (University of Massachusetts, Lowell, USA)

10:05
Segmentation of Drilled Holes in Textured Wood Panels using Deep Learning Framework
Muneer M. Al-Zubi (University of Luxembourg, Luxembourg & University of Technology Sydney, Australia); Peter Plapper (University of Luxembourg, Luxembourg)

11:00 - 12:40 (Europe/Berlin)
Body Attached
Chair: Rim Barioul (Technische Universitat Chemnitz, Germany & CEM Research Laboratory at the National School of Engineer of Sfax, Tunisia)

11:00
Dual-IMU-WIP: An easy-to-build Walk-in-Place System based on Inertial Measurement Units
Tom Uhlmann (Chemnitz University of Technology, Germany)

11:20
Early detection of Parkinson's disease by unsupervised learning from plantar bend data
Huan Zhao, Junxiao Xie and Junyi Cao (Xi'an Jiaotong University, China)

11:40
Real-Time Model for Dynamic Hand Gestures Classification based on Inertial Sensor
Achraf Djemal and Hiba Hellara (National School of Electronics and Telecommunications of Sfax, Tunisia); Rim Barioul (Technische Universitat Chemnitz, Germany & CEM Research Laboratory at the National School of Engineer of Sfax, Tunisia); Bilel Atitallah (Technische Universität Chemnitz & National Engineering School of Sfax, Germany); Rajarajan Ramalingame (Technische Universität Chemnitz, Germany); Ellen Fricke and Olfa Kanoun (Chemnitz University of Technology, Germany)

12:00
Classification of Dynamic Hand Gestures using Multi Sensors Combinations
Hiba Hellara and Achraf Djemal (National School of Electronics and Telecommunications of Sfax, Tunisia); Rim Barioul (Technische Universitat Chemnitz, Germany & CEM Research Laboratory at the National School of Engineer of Sfax, Tunisia); Olfa Kanoun (Chemnitz University of Technology, Germany)

12:20
A Hybrid Measurement System for Hand Signs Recognition based on EMG-FMG Measurements
Chi Liu (Chemnitz University of Technology, Germany); Bilel Atitallah (Technische Universität Chemnitz & National Engineering School of Sfax, Germany); Rajarajan Ramalingame (Technische Universität Chemnitz, Germany); Rim Barioul (Technische Universitat Chemnitz, Germany & CEM Research Laboratory at the National School of Engineer of Sfax, Tunisia); Achraf Djemal and Hiba Hellara (National School of Electronics and Telecommunications of Sfax, Tunisia); Olfa Kanoun (Chemnitz University of Technology, Germany)

14:00 - 16:00 (Europe/Berlin)
Machine Learning
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

14:00
Relevant P*arameters Identification in Traditional & Strech Blow Thermoplastics Injection Molding*

Bruno Silva (Polytechnic of Leiria, Portugal); Ruben Marques (Vipex, Portugal); Tiago Santos (Muvu, Portugal); João Sousa (Polytechnic of Leiria, Portugal); Guillem Alenya (UPC, Spain)

14:20
Evolutionary Simulated Annealing for Transfer Learning Optimization in Plant-Species Identification Domain
Gusti Ahmad Fanshuri Alfarisy, Owais Ahmed Malik and Wee-Hong Ong (Universiti Brunei Darussalam, Brunei Darussalam)

14:40
Random Walk Binary Grey Wolf Optimization for feature selection in sEMG based hand gesture recognition
Rim Barioul (Technische Universitat Chemnitz, Germany & CEM Research Laboratory at the National School of Engineer of Sfax, Tunisia); Rahul Raju (T U Chemnitz, Germany); Sebin Varghese (TUC, Germany); Olfa Kanoun (Chemnitz University of Technology, Germany)

15:00
Towards a Vowel Formant Based Quality Metric for Text-to-Speech Systems: Measuring Monophthong Naturalness
Sven Albrecht, Rewa Tamboli, Stefan Taubert, Maximilian Eibl, Günter Daniel Rey and Josef Schmied (Chemnitz University of Technology, Germany)

15:20
Heuristic Application System on Pose Detection of Elderly Activity Using Machine Learning in Real-Time
Sofia Ariyani (Universitas Muhammadiyah Jember, Indonesia); Eko Mulyanto Yuniarno (Institut Teknologi Sepuluh November, Indonesia); Mauridhi Hery Purnomo (Institut of Technology Sepuluh Nopember, Indonesia)

16:00 - 16:30 (Europe/Berlin)
Closing
Chair: Olfa Kanoun (Chemnitz University of Technology, Germany)

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Heuristic Application System on Pose Detection of Elderly Activity Using Machine Learning in Real-Time*

*Note: Computer Vision To Track Elderly Movement Automatically

1st Sofia Ariyani
Department of Electrical Engineering
Universitas Muhammadiyah Jember
Jember, Indonesia
sofia.ariyani@unmuhjember.ac.id

2nd Eko Mulyanto Yuniarno
Department of Computer Engineering
Department of Computer Engineering
Surabaya, Indonesia
ekomulyanto@ee.its.ac.id

3rd Mauridhi Hery Purnomo
Department of Electrical Engineering
Department of Computer Engineering
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
University Center of Excellence on Artificial Intelligence for Healthcare and Society
hery@ee.its.ac.id

***Abstract*—Many developed countries have a population of elderly people that is greater than the population of young workers. So. To meet the demand for labor there is a decline because many are retiring. To meet the future demand that many elderly people need a quality care service so that the elderly who experience physical and cognitive decline can be well protected.Great potential study and evaluation of elderly movement activity for healthcare. The algorithm of pose estimation takes advantage of recording video have tracked elderly movement automatically using camera devices and computer vision. Monitoring and measuring elderly movement activity in real-time more easily accessible with this view of technology offers a clear and exciting potential as motor assessment by the doctor at the patient at home. The perpetrator can send video recording directly in the field by combining expertise and perspective as from physical therapy insight into the application of pose estimation in human health, especially the elderly. This is focusing in a safe and comfortable way. These models use CNN and LSTM for classified labeling landmark point detection results with high performance 97,3 accuracy average and in real-time have range 30 FPS. So the heuristic application system can be recommended for monitoring the use of the camera with all its limitations**

***Index Terms*—Segmentation classification, pose estimation, behavioral activity recognition, Elderly movement tracking, machine learning, motion capture**

I. Introduction

Many developed countries have a population of elderly people that is greater than the population of young workers. So. To meet the demand for labor there is a decline because many are retiring. To meet the future demand that many elderly people need a quality care service so that the elderly who experience physical and cognitive decline can be well protected. The number of technologies that have emerged and allowed the elderly to be able to live longer in their own homes independently without a nurse accompanying them Economically this can save time and direct maintenance costs. Users can monitor the elderly through the sensor to detect ongoing dangerous situations, lifestyle changes, and emergencies that require an immediate response. There are two important factors so that the monitoring system can be accepted, namely instruction technology or information obtained in detail [1] The assessment of the behavior of the elderly is a reference point in monitoring daily activities directly. monitoring changes in the behavior of the elderly must be measured specifically, for example, about time, place, quantity duration, and frequency of this work, of course, is very complicated if done by family members and health workers because examining this in detail takes special time in providing assistance, even from an economic perspective as well. there are three behavior, appropriate behavior, and current behavior. recognition of human activities carried out using deep learning makes learning by imitating human neural networks. However, it is known that human visual recognition. Not focusing on the whole scene to extract relevant information at once [2], Instead, humans being scanned by the camera is a part of the information that has been extracted from a different sequence of activities. The computer vision algorithm still pays less attention to the mechanism of the image or video model learning process. Many of these models use RNN (Recurrent Neural Network) based on Long Short Term Memory (LSTM) and show very proud results in targeting in training. Noticed Visual models can be classified into soft models and can be trained using a reinforcement learning algorithm using Convolution Neural Network (CNN) [7]. Attention-hard models can be computationally expensive because they require sampling during training. On the other hand, in a soft attended approach, a distinguishable mapping can be used from the output of any position to the next input. Therefore, the amount of

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computation is less than the hard attention model. The basis of the model considered is the potential results of activities that occur in the video happening, so that focusing only on the relevant position of each frame. Therefore in this paper, we propose a late activity recognition algorithm in which the attention model soft visual preceded, the weight is increased to the relevant location, and the activity is recognized using visual data, and data through pose estimates are considered simultaneously.

II. KEYPOINT DETECTION IN COMPUTER VISION

A. Image Classification

Image classification is a grouping of objects based on certain classes so that we can do it easily in recognizing objects. The result of feature extraction can be classified into image class information that refers to a multiband raster image. The scores generated from the image classification can be used for thematic maps that depend on the interaction. There are two types of classification, namely supervised and unsupervised. With the algorithm described in detail, it is proposed using the input image from the video which is divided sequentially and visually attention performed as a result of the recognition based on appearance performed with the results of pose estimation using the input image also combined with the previous one in the following algorithm:

Algorithm Activity recognition procedure.
Input: N Video Frame
Outputs: Result of activity
1: for the introduction activity do
2: Visual attention-based activity recognition(N)
3: Activity recognition based on pose estimation(N)
4: Activity recognition based on appearance (N)
5: Aggregation
6: and for

B. Object Detection using landmark Points

The theoretical basis that can be implemented in detail in making a pose detection model uses 33 landmark points which can be seen as shown in the following figure 1.

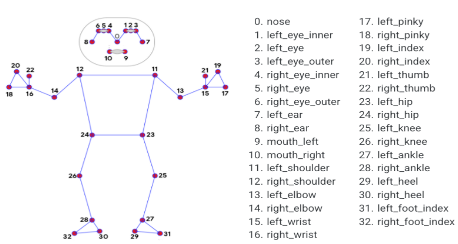

Fig. 1. Basic Human behavior pose detection using 33 associated landmark points in people's body.

C. Image segmentation

Image segmentation is the division of the image area into smaller areas based on the location of the pixels and their intensity that are still close together. It aims to group object pixels into areas that represent objects. The segmentation carried out in this study is color segmentation is an image segmentation method that separates objects from the background based on certain color characteristics of the object. One of the color segmentation processes can be done by converting the image color space which was originally RGB (Red, Green, Blue) into HSV (Hue Saturation Value) color. The Hue component is a component that represents the color of various wavelengths of light. The Hue component of the HSV color space is then extracted and divided into several color regions. The next approach is also carried out by entering a gray level image and the output is edge(binary) image to perform continuity detection, so the existing pattern model consists of point detection, line detection, and edge detection can use a mask/ kernel, different for each detection.

III. POSE DETECTION

Branch of computer vision are image recognition. Some other classes that are owned by computer vision are broader and their branches are detection and segmentation which are part of subsequent data synchronization for 3D pose estimation.

A. Data Sync and 3D Pose Estimation

Recent developments in deep learning have made it possible to learn powerful filters from datasets using a hierarchical system. In addition, filters learned from large datasets can be used as training data for the learning process so that insufficient data becomes less effective and becomes a problem in the learning. The Vnect approach proposed here [2] is one system that uses transfer learning for effective 3D pose estimation directly from RGB images. VNect is based on CNN pose regression which allows a real-time estimation of 2 D and 3D frames using RGB images. For each combined human joint estimate, the network was trained to estimate 2 D confidence of the mapping results together with the location map (for each of the three dimensions). One of the main advantages of 3D pose estimation is being able to estimate the position of the corresponding 3D point at different viewing angles. In this case, the alignment of the 3D poses can be approximated with a closed shape sequence.:

$$\underset{R}{ARGmin} \parallel X1 - RX2\|_2^2 \tag{1}$$

The above equation (1) has the form of a closed solution which is given;

$$R = UV^T \tag{2}$$

Where is $U\Sigma V^T = X_1 X_2^T$ U, and V are unitary matrices, and diagonal matrices according to the Single Value Decomposition (SVD) of $X_1 x X_2^T$. The matric R represents the expected rotation matrix. Given two sequences of n poses, estimated different points of the First one$X_1 = x_1 1 \ldots x_1 n$ and the second sub 2n, $X_2 = x_2 1 \ldots x_2 n$, we estimate the alignment to explain further, the x1 and x2 data are approximated, to the same 3D pose of the subject from two different viewpoints. Assuming, the average of the pose estimates is carried out with the approximate rotation R through the following optimization poses subscript base, in base, x sub, 11 in, x sub, 12, end subscript, $x_1 1 x_1 2$ using equation (2). After that, the approximated rotation of the R matrix is used to align the rest of the next poses of the sequence.

B. Pose Sequence Modeling

In general, if the data used is RGB data, then during the training process there will be noise in the dataset in the 3D pose estimation model. This can be solved by using an LSTM-based temporal model to estimate pose detection in noisy frames.. There are two components: (1) a feed-forward network to expand the data into a high-dimensional space, and (2) a multi-layer LSTM unit to model the temporal dependencies, as shown in figure 2. First, a description of the data expansion. The 3D framework is estimated with J the number of joints is a vector in k3J. Therefore, the noisy co-estimate is directly reflected in some of the observed dimensions of the vector. One typical solution to eliminate noise and redundancy is to contract the data to a lower-dimensional space [2]. Instead, in this paper, the data used is expanded to a higher dimensional space. The first motivation for expanding the data is to unravel the explanatory factors obscured by noisy co estimations. As a result, the parameters of the expansion function are studied directly from the training data set. The extension of the observed framework is defined as follows:

$$x = tanh(Wx + b) \tag{3}$$

Where W is a kx3J matrix with k3 J, b is the bias vector in the k-dimensional space, and x represents the extended pose approximation. The second is the temporal model description and activity labeling. The temporal dependence between sequential data points is modeled using the LSTM unit layer [3]. The LSTM is a gated recurrent neural network that models temporal dependence as a stationary process. Furthermore, given the expanded input data x the estimation used in this paper, the hierarchical latent variable by layering the LSTM units one on top of the other is shown in Figure 2. As a result, the latent space h sub, inferred L, i., equals; pose estimation is given as

$$h_L i = LSTM(x_i) \tag{4}$$

Where L represents the index of the last LSTM layer. Finally, the activity label of the set is assigned to the sequence as

$$\Psi = argmax(tanh(W_n^L + b)) \tag{5}$$

$$\Psi \epsilon \psi \tag{6}$$

Where n is the index of the last pose estimate. ψ is the set of activity labels, y is the activity label that can be generated as result, and Ψ is is the last defined activity label. Weights and biases of the entire network to connect the model expansion transient data are trained together by minimizing the cross-entropy between predicted and given probabilities of activity labels through backpropagation and backpropagation through time [2]. In the figure below, it can be seen that each joint

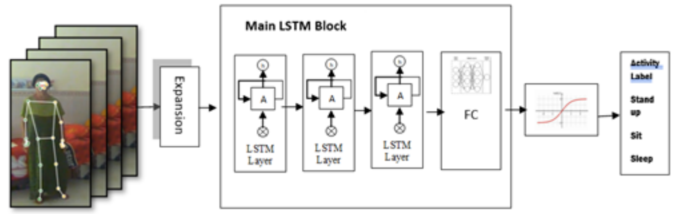

Fig. 2. Activity Recognition Uses Pose Estimation, Refers to The Fully Connected Layer at The End of The Main LSTM Block.

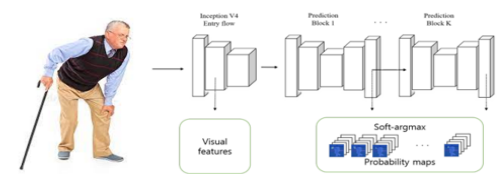

Fig. 3. Visualization of Prediction Diagram Block Algorithm CNN Based on Visual Features Used Probability Map Extraction with Regression Approach of video frames.

represents the human skeleton. It uses VNect, and when the pose estimation results and RGBbased results are combined as a result, the accuracy of similar movements that cannot be properly classified is improved.

C. Model based CNN

In Figure 3. Visual features and probability maps are extracted using CNN. The convolutional layer process containing kernel with certain dimension. Dimension size 64x64 pixel or 28x28 pixel and then image scanning to perform extraction features. The convolutional operation is dot product between weight in the filter and kernel and the pixel value observed by the filter and then summed. In this model used 3 layer convolutional with activation function Rectified Linier Unit (RELU). In the pooling layer used to reducing the numbering feature will increase effectiveness model training. Model network continue to dense layer (fully connected) as function to classify according to the class in the output. One input has an output correspond to the number of classes to be predicted. The first network, and a probability map associated with each prediction block up to end is extracted. The result from CNN used as an input for LSTM.The clarification process and feature extraction need to be carried out starting from the lowest level to the highest level which is apart of the body and becomes a probability map of input frames related to a joint input sequence in introducing activity recognition [8].

D. Real-time Pose detection

The results of image detection are quite good and now we are traying its function on the webcam camera in react time and video. Running pose detection on video stored on disk or on a webcam feed can provide the video capture object initialization code. Video stored on disk or directly

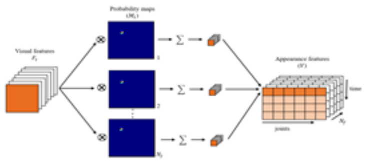

Fig. 4. The Flow of Model from The Input Extraction Feature to The Introduction of Recognition of Activities Based on Appearance With Visual Level Features and One Part Body Probability Map Based on the Frame Sequence That is Part of The Correspondence Input Frame.

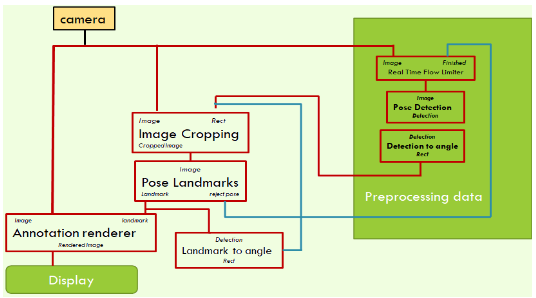

Fig. 5. Block Diagram of The Equipment Used In The Pose Detection Model Using The Camera

via webcam can provide initialization code to capture video objects that can be run directly by running pose detection on a computer using python language according to pose estimation algorithm with syntax from open pose, deeplabcut,deeperpose, alphapose, and arttrack. This can be done in advance, data preprocessing can advanced use the pre-training network, so that the new training data is used as learning therefore it can adapt according to clinical needs or from different research. In general pre-trained human open poses are used as a demonstrated pre-workout network to cover important body points, legs arms, face, and some recently studied for quantitative analysis of human movement. The computations required for new network sets and new video tracks are often computationally intensive. So that the computing power of Graphic Processing Unit (GPU) can allow processing times to be reach acceptable limit from several algorithms providing documentation with hardware recommendations. Processing uses a slower CPU but may be sufficient depending on time constraints and user processing needs.

E. Result And Discussion Of The Framework

Behavioral pose detection in real-time can be achieved by using pose detection models that are arranged in building blocks and optimal throughput in the Machine learning pipeline. There are several important steps that must be carried out in the following this

- Initialization Of The Behavioral Pose Detection from Elderly Activity The first thing to do when detecting activity poses from an elderly activity is to initialize pose class using the syntax mp.solution.pose and then set up function mp.solution.pose.Pose() with arguments:static_image_mode, this boolean syntax is set to the detector if it is set to false then it is called only as needed the first it is framed or when the tracker losses track. If set to True detector is only called as needed the first time is framed or when the tracker loses track. If set to true then the person detector is called on every input image. So this value is set to True when working with a set of related images instead of videos. The default value is False. Confidence of Detection_min. which is built is minimum detection confidence with a range of conditions (0.01.0) this is needed to consider the prediction results of the elderly detection model to be true(valid). The default value is 0.5. meaning that if the detector has predictive confidence greater than equal to 50% it will be considered a positive detection. Min_tracking_confidence.this is the minimum detection confidence (0.01.0) required to consider that the tracked poses landmark tracking model is valid. If the built confidence is less than the set value then the detector is called again in the next frameimage so as to increase its value, increasing robustness, but also increasing latency, and the default value 0.5. The complexity of this pose model in the landmark. Since there are three different models to choose from, the possible values are 0.1, or 2. The higher the value the more accurate the result, but at the expense of higher latency. The default value is 1. Smooth_landmarks this is a boolean value which when set to True, the poses of landmarks in various image frames will be filtered to reduce noise. But it only works when static_image mode is also set to False. The default value is true. Then the mp_solution_drawing_utils class allows visualizing the landmarks after detection by trying to use this and also using Open CV to visualize the landmarks. How to read an image using the cv2_imread() function then display an image using matplotlip, and pass the image to the pose detection machine learning pipeline by using the function mp_solution.pose.Pose().process()But pipe expects insert image in RGB color format so first, the sample image must be converted from BGR to RGB format using the function. cv2.color() comes from Open CV to read images in BGR format (not RGB). After detecting poses with 33 landmark points that represent the location of the most prominent joints of the person's body in the image each process has: X: is the xcoordinate of the landmark representing the width of the image normalized to (0.0,1.0) Y: is the y coordinate of the landmark representing the image height with normalized (0.0,1.0) Z: is the z coordinate of the landmark which represents an approximate scale equal to x and represents the depth of the landmark with the midpoint of the hip as the origin so the smaller the z value the closer to the camera landmark. Visibility is a range value(0.01.0) that represents the likelihood that a landmark is visible (unobstructed) in the image. The results of the implemented heuristic application system can be seen in Figure 6. As a result of landmark visualization from pose detection estimation [**?**].

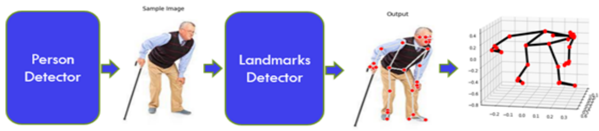

Fig. 6. Model of the work image detection poses for one personal elderly

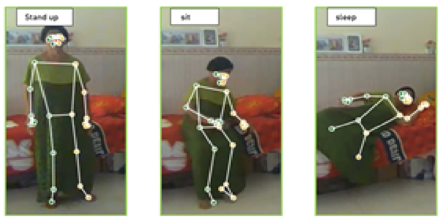

Fig. 7. Image Labeling from landmark point detection result

- Creating A Detection Function Calculation of the angle between 3 landmarks by creating a function of the angle between two lines. The first landmark point is considered the starting point of the first line, the second point is considered the point of the first line, and also the starting point of the second line, and the third point landmark is considered the endpoint of the second line. To visualize a landmark in three dimensions (3D) using function mp_solution;drawing_utils:plot_landmark() and need function poseworld_landmark which is another list of landmark poses in world coordinates having 3 D coordinates in meters with nose in the middle between the person's hips. That actually this is a neat hack by media pipe, the actual coordinates are not in 3D but by setting the hip landmark as defined which allows measurement of distance relative to other hip points, and as distance increases or decreases depending on whether you are near or far from the camera, this describes the depth at each landmark point. By utilizing the function created to perform pose detection of several sample images and display the results. If we want to expand it again in the form of a classification function with more poses as in figure 7. Below is the pose of the elderly with an activity label.
- Training data Frame generated from video rendering are collected to classified manually into 3 types of elderly body poses then used as training data using CNN-LSTM model as many as 1632 and for each type of pose there are 408 image data while the test data also has 3 types of activity detection and for each pose detection there are 136 image data. The training process is carried out by entering the data set into the model to be trained until it gets the best weight with good data accuracy validation with adaptive learning results obtained iteration results of up to 50 epochs are shown in the graphic as shown in figure 8. Each curve represents datasets evaluations spread evenly throughout 50 epochs of training on data

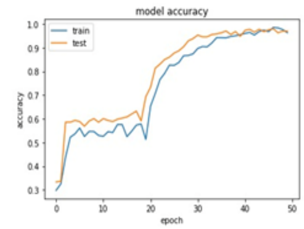

Fig. 8. Graphics Accuracy and score of the data in The Validation set of Accuracy

set but these model accuracy data tests learn significantly faster than train data. In addition, an increase in accuracy occurs in the accuracy value between 59% to 98,75% namely with training data and test data at 20 to 50 epochs. The average level of accuracy obtained the same value when the training data and test data are 97,06% with 50 epochs. The best results were obtained based on the test results of the image data shown in figure 9. The CNN-LSTM model produces a graph of the loss function value on the training data showing epochs 1 to 18with loss value ranging from 1.2 % - to 0.8%. Meanwhile, the training data starts from 19 to 50 epoch with the loss function value getting smaller which is between 0.65% to 0.045%. While the loss value is influenced by the amount of data used in the training process so that it has a very good accuracy value. That the test data on the loss function graph shows a lower loss value of 0.1 % by ending in the same epochs at a value of 50.

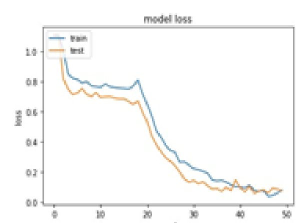

Fig. 9. Graphic loss function and score of the data in the validation set loss

- Testing data The pose detection process is carried out starting from preprocessing the data used as training data in the training model derived from the pose detection video data directly and randomly using the size per frame with a resolution of 225x144 which is captured at a speed of 30 Frames Per Second (FPS) this is a good performance for real-time measure. Once every 3 seconds, the results of the pose detection are recorded. There are 3 types, each of which produces 136 image frames, so that total is 408 image frame which are used as test data. end document The result of the performance matrix from the data testing process are shown in the table 1. The previously created dataset has been carried out as test data showing best optimization results. The average level of accuracy in online testing is shown at a value 97.3%. This results is good but the level of accuracy

TABLE I
PERFORMANCE CONFUSION MATRICS OF THE DATA TESTING RESULT OF POSE DETECTION

Type of pose detection	precision	Recall	F1 score	support
Stand up	1.00	0.98	0.99	136
sit	0.98	0.95	0.97	136
sleep	0.93	0.99	0.97	136
accuracy			0.97	408
Macro avg	0.97	0.97	0.97	408
Weighted avg	0.97	0.97	0.97	408

needs to be improved. The learning model created still needs to be tested again using a random and varied background.

F. Application Limitations and Discussion

- Occlusion: this event occurs when the anatomical location of the human body being tracked is not visible to the camera from the result, the other body segments in one frame of objects from elderly or other object detection because of different location.
- Limited training data: the training data sets in the image frame are related to results from pose detection it is related to an image data frame that is including the condition of the cloths and the condition of the human body, is it healthy or has had a stroke, so this is a non-variable that is not associated with pose detection in elderly activities whereas the joint angle position formed between joint is less perfect and it can be seen when the body is covered by long clothes, the detection results are less than perfect, this affects the training of the data and indeed to improve the detection results.
- Capture error: when the camera records a human body tracking video using a pose estimation algorithm, unwanted fields of view are sometimes included in the frame including the background and the large poster in the frame too.
- Positional error: the condition of a person's body may be difficult to track because a less than the optimal point of view can occur because the movement of the anatomy of the body is not perfect for example when sleeping lying down, the zero point is not found on the nose so that the joint point landmark cannot look perfect as a whole because it only looks like part of it. The angle of the foot cannot be seen.
- Limitations of recording equipment: sampling video when recording using camera equipment that has a high-speed resolution and low-speed resolution will certainly produce different values, of course. Often when video recording uses a frequency of 30 HZ, it affects image quality and tracking results in estimating pose detection.
- Outcome measure challenges: In many cases, the movement activity of the human body can be used as the performance of pose detection results, by using the data from this detection it can clearly be used as a related parameter in clinical trials by doctors in knowing a person's gait including normal or abnormal elderly. So that the most relevant can be recommended by a doctor in observing the motion of human behavior.

IV. CONCLUSION

The development of pose detection of elderly behavior has very interesting potential in making quantitative assessments of the kinematics of elderly movements significantly more accessible. Pose detection is the result of pose estimation that can directly answer the important and widespread need for this technology at a very low cost in tracking a movement and can be accessed directly in almost any environment including inside and outside the home. To validate the performance of machine learning deep learning, the data set from the pose detection landmark point was evaluated. The performance of the proposed method, specifically CNN and LSTM showed outperformed classifier in real-time for classifiers and label activity from detection pose ranges FPS 30, which required the simple architecture machine with high performance in the classification of pose detection have 97,3% average accuracy rate. So that heuristic application system can be recommended using a camera for monitoring the elderly.

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