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Abstract— **Mild Cognitive Impairment (MCI) is a definition of the diagnosis of early memory loss and disorientation. This study aims to identify people's symptoms through technology. However, machine learning (ML) can classify Cognitive Normal (CN) and Mild Cognitive Impairment (MCI) and Early Mild Cognitive Impairment (EMCI) using standard assessments from the Alzheimer's Disease Neuroimaging Initiative (ADNI); Montreal Cognitive (MoCA), Mini-Mental State Examination (MMSE), Functional Activities Questionnaire (FAQ). Consequently, a Multilayer Perceptron (MLP) model was assembled into tables; MCI vs CN, MCI vs EMCI, and CN vs MCI. Additionally, an MLP model was developed for CN vs MCI vs EMCI. As a result, of advanced model performance, a cascade 3-path categorisation approach was created. Similarly, the exploitation of meta-analysis indicated a combination of MLP models (MCI vs CN, MCI vs EMCI, and CN vs MCI) with an overall accuracy within an acceptable limit. In addition, better results were found when assessments were combined rather than individually. Furthermore, applying class weights and probability thresholds could improve the MLP framework by performance achieving a balanced specificity and sensitivity ratio. Altering class weights and probability thresholds when training the MLP neuro network model, the sensitivity and Accuracy could be progressed further. In conclusion, ML, VR and electrodermal activity are constrained. Introducing the possibility of activity-based applications to enhance innovative solutions for cognitive impairment diagnosis and treatment.**

Keywords— Mild Cognitive Impairment, Machine Learning, Neuropsychological Assessment, Virtual Reality, Electrodermal Activity

I. INTRODUCTION

5 to 20% of the UK population and almost 15-20% of older adults aged 65+ are diagnosed with Mild Cognitive Impairment [1, 2]. MCI exists between the cognitive changes of normal ageing and dementia. The classification of MCI is based upon Amnestic MCI (individuals affected from memory loss and may forget important information; appointments, events, or conversations) or Nonamnestic MCI (individuals affected from other abilities, including making decisions, visual perception and determine time). Cognitive Impairment signs include attitude and behavioural variations, confusion, and individuals become incapacitated, unable to support themselves or perform daily activities [2, 3]. Hence, detection and rehabilitation applications for individuals at a greater risk of developing mild cognitive impairments are global priorities [4, 5]. While there is growth in research within the health industry and educational field, few established effective therapies for mild cognitive impairments [6–10]. Subsequently, there is a need to develop techniques and applications to support the identification of mild cognitive impairments. Since early detection of cognitive impairment symptoms is the most efficient way of handling, reducing, or improving disorders such as anxiety, depression, and stress [11–13]. A collection of three types of older patients are encompassed in this machine learning categorisation study: Cognitive Normal (CN) and Mild Cognitive Impairment (MCI), and Early Mild Cognitive Impairment (EMCI). A subject with cognitive normal has no symptoms of mild cognitive impairments; instead may suffer from other age-related diseases. A patient with CN can alter to MCI when conditions become more evident to the individual, family, friends, or medical staff. MCI is the intermediary phase amid CN and EMCI, and medically is the first measurable stage of advancement towards early-onset dementia [8]. Individuals diagnosed with anxiety, depression and stress are at increased risk of developing MCI symptoms and progression to dementia and other types of the disease. Alzheimer's disease is the final phase of deterioration.

In comparison, Alzheimer's Disease has given more attention in Alzheimer's Research and Therapy, vol. 10, no. 1, 2018 and in 2019 by Spasov et at al. [14, 15]. There has been much research in the medical industry because of growth in prompt propagation of qualitative and quantitative biomedical datasets, simultaneously being implemented with various machine learning techniques. Notably applying deep learning [1, 16]. Advances in research have broadened the scope for developing applications and diagnostic software to detect mild cognitive impairments. Several experimental studies investigated the prevention, prediction of cognitive impairments using different subjects by exploiting various entities of biomedical metadata, including using electrodermal activity (psychological, physiological, and behavioural) and brain imaging [7, 17–19]. There has been much research in the medical industry because of growth in prompt propagation of qualitative and quantitative biomedical datasets, simultaneously being implemented with various machine learning techniques. Notably applying deep learning [1, 16]. Advances in research have broadened the scope for developing applications and diagnostic software to detect mild cognitive impairments. Several experimental studies investigated the prevention, prediction of cognitive impairments using different subjects by exploiting various entities of biomedical metadata, including using electrodermal activity (psychological, physiological, and behavioural) and brain imaging [7, 17–19]. Standard neuropsychological assessments are generally applied in diagnosing cognitive impairments symptoms in individuals with MCI, EMCI and more disorders (anxiety, stress and depression) [11, 12, 20, 21]. These assessments are cost-effective, simple to perform and widely available online compared to MRI imaging [22]. These methods can gauge abnormal and normal behavioural and cognitive activity that offers valuable attributes for machine learning techniques for the early recognition of Mild Cognitive Impairments [4, 9, 23]. Repetitive tests of these assessments for analysing any changes in individual circumstances over time in therapy [18]. Various cognitive impairment symptoms signify that applying several neuropsychological assessments from various fields may enhance diagnosis accuracy[1, 15, 23]. In this paper, presented is a multi-layer perceptron (MLP) neuro network to execute binary categorisation of various cognitive classes (CN vs MCI vs EMCI) applying a baseline patient metadata from three neurophysiological assessments from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database [24]. An additional precise MLP built 3-path (CN vs MCI vs EMCI) categorisation is applied. Furthermore, this study recommends a waterfall MLP approach to expand and improve the multi-categorisation implementation. This paper is consolidated into the following: 1) Introduction, 2) Related Works, 3) Tools and Techniques, 4) Results and Discussion, 5) Conclusion and Future Work.

II. RELATED WORKS

Present research looks to apply quantitative data collection and evaluating numerical meta-analysis because it provides the opportunity to widen the examination and frameworks for comparison to understand the changing aspects of VR better, EDA concerning randomised clinical trials [37 - 38]. The growth in VR and EDA in Society and the development of the healthcare industry have seen the requirement for innovation in applications that can assess patients' needs and identify the most appropriate solution for their health is becoming more exciting. Real-time assessment is particularly important in fields such as education, healthcare, sports and the commercial industry. A framework that can detect MCI using health data with higher accuracy is an important topic that could lead to further health and emotional benefits. Offering more information about MCI to people susceptible to anxiety, depression and stress and psychological assessments are examples of how beneficial MCI support detection is [8, 15, 35]. The possibility of testing different individual data sets with methods collected using a sensor scanning various signals may help improve the framework's accuracy and reliability. VR makes it possible to study such environments under controlled clinical conditions. otential challenges were highlighted by Hsieh et al. and Gold et al. in 2018, who identified innovation in technology with these frameworks; they should be implemented in the healthcare industry [39], [40]. This type of implementation is the financial implication of hardware, software integration and connection to hospital databases and equipment for staff and individuals, making it simpler to utilise and support MCI and long-term application heath. Moreover, training recruits and patients are probable issues and challenges going forward. However, Gold also stated it was more important to maintain standard hygiene processes to reduce patient infection and share technology [39], [40]. Whereas Weech et al., in 2019, was more concerned with the measurement authenticity and cross-validation of the measurement system. Studies involving MCI to date have concentrated on awareness for adults or those with MCI. However, there has been an increase of patient-centric support groups who later become representatives of healthcare teams who can then voice their own opinions about treatment [42].

III. TOOLS AND TECHNIQUES

In this section, an overview of the main tools and techniques applied in the study.

A. Virtual Reality

Oculus Quest's recent developments for VR, signal processing for electrodermal activity, machine learning algorithms could provide long term solutions to support cognitive impairments [2–5]. In addition, these tools could improve diagnosis and therapy and contribute to the disorder's detection [6, 7]. VR is becoming a revolutionary way for integrating computers with IoT. The equipment eliminates customary partition among devices and users. One example is the work of John et al. who developed a virtual environment named VIRTUE for cognitive rehabilitation of stroke survivors [26]. They conducted a study using forty patients from the Stroke ward of a local hospital and found those more severely affected by a stroke demonstrated better recovery through use of VR therapy. There was also a reduction of the time patients stayed in the hospital. It is anticipated that other groups of people with cognitive impairment (including anxiety, depression and stress disorders) can also benefit from VR therapy.

B. Electrodermal Activity

Innovation in recent wearable devices support constant and prominently observing individual physiological parameters such as electrodermal activity, heart rate and sweat glands in everyday life over time-consuming intervals. Uninterrupted monitoring of such parameters facilitates predicting mental states and stress, intending to deliver responses to enhance the results. However, the utilisation of these applications in the real world is still convoluted and susceptible to error handling issues because of poor quality data collection, which influences objects' existence in this survey a machine learning approach to detect features automatically using electrodermal activity sensors which can be gathered in VR and the real-world. Intrinsic active modifications permit various measurements to be captured using several bio-signals. These sensors provide time-altering indicators for the human brain's cognitive state through physical and psychological accuracy [23]. The electrodermal activity has bio-signals that include skin conductance and changes in acceleration, pressure, sound, flow, and temperature [16].

C. Metadata

The metadata applied in this study was acquired from the Alzheimer's Disease Neuroimaging Initiative; ADNI-2 from September 2011 for 5 years and the ADNI-3 in September 2016 for a further five years [24]. ADNI-3 involved researchers from 59 institutions from the US and Canada. 1070-2000 participants were enrolled; 700-800 were existing participants from ADNI-2, and a further 370-1200 new individuals were registered, as illustrated in Table 1. Cohort size of the study. These two phases, including follow-up sessions, have engaged adults, ranging from 50 – 90 years old, comprising three cohorts: Cognitive Normal, individuals with MCI and EMCI [24, 25].

TABLE I. COHORT SIZE OF THE STUDY

Stage of Participant	*ADNI-2*	*ADNI-3*
CN	295-330	135-500
MCI	275-320	150-515
EMCI	130-150	85-185

TABLE II. ASSESSMENTS APPLIED ON PARTICIPANTS

Assessments	
MMSE:	Orientation Registration Recall Language Visual Construction Attention & Calculation
MoCA:	Visuospatial & Executive Naming Memory Language Abstraction Delayed recall Orientation
FAQ:	Q1. Manage finances Q2. Complete forms Q3. Shop Q4. Perform games of skill or hobbies Q5. Prepare hot beverages Q6. Prepare a balanced meal Q7. Follow current events Q8. Attend to TV, books, or magazines Q9. Remember appointments Q10. Travel out of the neighbourhood

1) For papers with more than six authors: Add author names horizontally, moving to a third row if needed for more than 8 authors. *Participants:* In this study, the baseline participant distribution data from a total of 2580 participants at an initial project period (ADNI-2 and ADNI-3), including 810 CN, 663 MCI and 340 EMCI. The registered participants were between 50 – 90 years old (wide-ranging), were healthy, and having carers who were able to communicate an in-depth health assessment of the participant's capabilities, with the ability to translate in either Spanish or English and who had a full work history or at least a Year 7 (Grade) education. All participants and their carers provided their consent. The Institutional Review Board reviewed the methodology for all ADNI data locations [24]. Table 2. Attributes of participants illustrate the results of assessments of the CN, MCI and EMCI participants involved in this study. The mean test scores were processed in Jupyter Notebook with Python (statistics module's mean() function) and averaging the scores from the enrolled participants from the original dataset.

TABLE III. ATTRIBUTES OF PARTICIPANTS

Attributes	Minimum/Maximum	*Mean*	*Std Deviation*
MMSE Score	10/135652	24915.832	37105.836
MoCA Score	6/135649	24475.467	37489.028
FAQ Score	5/135602	26274.629	39151.813
Visit per Assessment	0/184	30.73	57.108
Visit per Demographic	0/839	195	216.708
Visit per Participants	0/1589	355.595	401.331
Values are shown as mean ± standard deviation or gender ratios. The p-values for differences between CN, MCI, and EMCI are based on t-test. MoCA = Montreal Cognitive Assessment; MMSE = Mini-Mental State Examination; FAQ = Functional Activities Questionnaire.			

2) *Assessments:* The enumerated scores of the three neuropsychological assessments applied, including Montreal Cognitive Assessment (MoCA), Mini-Mental State Examination (MMSE), and Functional Activities Questionnaire (FAQ). Table 2 illustrates the everyday cognitive events linked with individual assessments. Overall, there are 7, 7, and 10 questions from MMSE, MoCA, and FAQ, correspondingly. The score of each individual question is treated as an element in the created machine learning activity, resulting in a total of 7, 7, and 10 features for the MMSE, MoCA, and FAQ metadata. The three neuropsychological assessments are generally used to aid cognitive impairment in MCI. The most prominent feature of MCI is memory impairment. Therefore, MMSE and MoCA assessments were applied in this study. MMSE and MoCA can assess global cognitive tasks as well as several domains other than memory. Information on function from the FAQ assessments were included to provide functional changes that may appear earlier in the MCI process.

D. Experimental Design for Classification

An MLP was created using original metadata features from the neuropsychological assessments (MMSE 7, FAQ 10 and MoCA 7) and the merged assessments of 60 features from the three neuropsychological assessments. First to be trained were three binary classifications between various cognitive classes for individual assessments and combined assessments: (Task 1. MCI vs CN, Task 2. EMCI vs MCI, and Task 3. EMCI vs CN. The recommended waterfall MLP process consisted of two stages. In the first part, classification of CN vs (MCI and EMCI) with an MLP neuro network. Training an additional MLP neuro network with the predicted

CN or MCI samples from the first step to classify CN vs MCI in Stage 2. Note that the true CN samples unclassified in Stage 1 as (MCI and EMCI) will participate in the second stage and will be calculated as unclassified CN regardless of their predicted results in Stage 2.

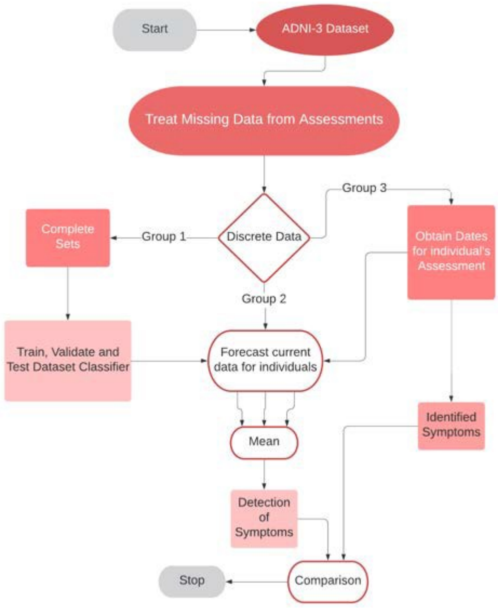

Fig. 1. Workflow of experimental design

E. Pre-processing

The original baseline visits in ADNI-2 and ADNI-3 consist of CN=810, MCI=663 and EMCI=340. Five participants were removed because of null data. Thus, the data in total was CN=809, MCI= 662 and EMCI=340. Ensuring experimental study did not have any missing age gaps, using only an age range of between 50-90. Missing values were dropped because the sample size was quantitative, and the number of fields did not exceed more than 5% of the overall sample. However, the three assessments did have special characters (=,",.,?,!,-,&) in various fields. These were all removed, allowing conversion from CSV to Arff for pre-processing. Feature normalization was executed by standard scaling with zero mean and standard deviation equal to one.

F. Partitioning

Cross-validation (CV) with Linear Regression was used to evaluate the predictive model. Data was split into ten disjoint subsets with consistent ratios between classes in each fold. 60% of the data was applied for testing in each fold. Leaving 40% for testing and validation purposes.

G. Multilayer Perception Neuro Network (MLP)

A multilayer perceptron (MLP) is a feed-forward artificial neuro network which applies back-propagation to revise weights. The neurons are linked to subsequent layers in a process that pushes data or information from the input to the output. MLP controls a layered framework of stacked perceptron's to resolve complicated frequently supervised, computational issues. The MLP can approximate non-linear functions for classification and regression. In this paper, a proposed methodology has been developed using multiple MLP neuro networks that are fully connected and can classify different cognitive classes (CN, MCI, EMCI) using three neuropsychological assessments. Figure 2 illustrates the 3layer MLP neuro network that can be applied to classify CN and MCI patients. For example, if combined assessment data were applied, the MLP model would have 53 nodes in the input layer, six nodes within the hidden layer and one node as an output layer. The Rectified Linear Unit (ReLU) was chosen as the input and output layers [20]. The sigmoid function and binary cross entropy were applied for the multi-class classification.
The SoftMax function and the multi-class entropy were applied for the multi-class classification. The adaptive movement estimation was applied as an optimiser to adjust the network during training. [18, 26]. The cross-entropy loss function was applied to quantify the MLP model for errors. Whereas the probability threshold as a criterion is another consideration. For example, an element could forecast to have a probability of 0.45 to be a category 1 and 0.55 to be a category (). If the probability were set to a default of 0.5, the element would be defined as a category (). If the probability threshold were established as 0.4 as an alternative, the element would be defined as a category 1. In this study, the framework applied training to include category weights and probability thresholds as constraints to reduce imbalance issues in the MLP model (specificity and sensitivity). L2 regularisation was deployed in the hidden layers to prevent over fitting. The regularisation strength for each layer was adjusted as a constraint. EarlyStopping function within Keras was applied through monitoring the loss function on validation of the collection

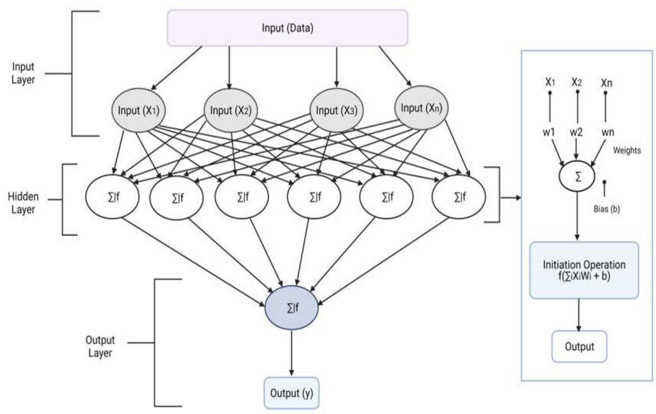

Fig. 2. Diagram of a 3-Layer MLP Neuro Network. Circles represent artificial neurons. Arrows represent connectors from neuron output to input

IV. EXECUTION EVALUATION

To scrutinise the performance of classifiers: Accuracy, Sensitivity and Specificity were measured for each mode. Sensitivity calculates the ratio of actual positive participants to the number of participants identified by the assessment as positive, for example, true positive rate. Specificity calculates the ratio of actual negative participants to the total number of participants testing negatively, for example, true negative rate. In comparison, Accuracy is the ratio of correctly classified participants to the whole set of participants. In-depth, this means Accuracy, Specificity and Sensitivity are better known as TP (True Positives), TN (True Negatives), FN (False Negatives), and FP (False Positives). This study will also measure the Area Under the Curve (AUC) from the Receiver Operating Characteristic (ROC) to demonstrate the classifier's diagnostic capability. The AUC was applied as a target metric for the duration of the hyper-parameter tuning. A result nearer to one implemented using an algorithm indicates a bordering on faultless execution. This result would mean it would become a more reliable predictive model.

V. RESULTS AND DISCUSSION

Figure 2 and Table 3 encapsulates the performance of a 3-path classification combining binary by applying each neuropsychological assessment (MoCA, MME and FAQ), including using these assessments to differentiate various cognitive classes (CN, MCI and EMCI). Default class weights were set to 1:1:1 for the 3-path classification or 1:1 for the binary classifier. The default probability threshold was set to 0.5. Table4 illustrates the MLP approach applied a combination of these three assessments to outperform the model using the individual assessments. The classification of CN and MCI participants had an increased accuracy of (98% -100%) in the models. These results indicate that the proposed MLP approach applying neuropsychological assessment data categorises CN and MCI. The classification of CN and EMCI was 77% - 82% when applying an individual assessment but achieved 90% when assessments were merged MCI and EMCI were more challenging because of classification. However, the overall Accuracy was within acceptable limits of 80% - 85%., sensitivity was weak at (47% - 69%) when applying an individual neuropsychological assessment. Whereas sensitivity was significantly improved to 81.4% when applying the merged assessments. The class weights and probability thresholds could be applied to improve the MLP approach through performance and achieve a superior balanced specificity and sensitivity ratio. By modifying the class weights and probability thresholds when training the MLP neuro network model, the sensitivity and Accuracy could be progressed further. For example, the sensitivity of MCI and EMCI increased from 46.81% to 79.26%. MoCA assessment increased from 81.38 to 91.49% with the merged assessments. The Accuracy of CN vs MCI vs EMCI increased from 82.43% to 84.28%.

Whilst the 3-path classification accuracy is particularly lower than the binary classifications. It did outperform other existing methods. For example, the Accuracy was higher than Lee et al. in 2019 [27]. Generic neuropsychological assessments are frequently integrated into normal routine physical medical check-ups for older adults. This study validates that early detection of cognitive impairments is achievable when applying these assessments with machine learning techniques like neuro networks. The prototype approach is valuable in supporting the classification of various cognitive classes that do not entail medical assessments and treatments currently more costly, intrusive or not provided in medical environments. Medical assessments and treatments include genetic testing, neuroimaging and cerebrospinal fluid (CSF). This experimental study identifies that applying a combination of neuropsychological assessments and tests used for MCI diagnosis enhanced the Accuracy of medical diagnosis. Finally, this study identifies the potential for MLP neuro networks to assist sort in discriminating between MCI progression classification. The growth in VR and EDA sensors in society and the development of the healthcare industry have seen the requirement for innovation in applications that can assess patients' needs and identify the most appropriate solution for their health is becoming more exciting. Real-time assessment is particularly important in fields such as education, healthcare, sports and the commercial industry. A framework that can detect CI using health data with higher accuracy is an important topic that could lead to further health and emotional benefits. Offering more information about CI to people susceptible to anxiety, depression and stress and psychological assessments are examples of how cognitive support detection could be beneficial.

VI. CONCLUSION AND FUTURE WORK

Existing studies investigating mild cognitive impairment detection applying machine learning approaches focused on electrodermal activity sensors (psychological, physiological and behavioural) and brain imagining metadata. The medical industry currently uses generic low-cost, widely available standard neurophysiological assessments. This paper analysed the classification of execution for detecting various cognitive classes (CN, MCI and EMCI) applying MLP neuro networks. Several key points can be concluded from the results identified. Using only one neuropsychological assessment to identify and gauge cognitive impairment symptoms and behaviour was very difficult and time-consuming. Secondly, combining three neuropsychological assessment metadata with an MLP neuro network indicates the possibility of growth through detecting and predicting cognitive impairments. The additional approach using MLP classification achieved baseline results on all three binary instances with a blend of assessments, including for the 3-path classification. Lastly, the recommended waterfall MLP method could additionally expand the execution of multi-class classification.

VR is becoming more enhanced with machine learning integration altering how it is developed. By understanding cognitive impairments, applications in VR will improve understanding and develop superior technologies. The proposed approach is scalable, cost-effective, more efficient, and can support screening of cognitive impairment diagnosis. Future work identifies individuals with cognitive impairment symptoms with disorders (anxiety, depression and stress) using machine learning, virtual reality and electrodermal activity sensors. Highlighting individuals who would be more vulnerable in developing MCI from CN within a distinct period. Other areas of interest for research include artificial neuro networks and unsupervised learning methods for prediction and rehabilitation purposes. Additionally, combining MRI imaging with virtual reality, behavioural data and machine learning may offer insights into identifying triggers and phases of cognitive impairments.

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