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A Home for Principal Component Analysis (PCA) as part of a Multi-Agent Safety System (MASS) for Human- Robot Collaboration (HRC) within the Industry 5.0 Enterprise Architecture (EA)

1st Anushri Rajendran
IISR
Deakin University
Geelong, Australia
arajendran@deakin.edu.au

2nd Parham M. Kebria
IISRI
Deakin University
Geelong, Australia
https://orcid.org/ 0000-0001-7049-928X

3rd Navid Mohajer
IISRI
Deakin University
Geelong, Australia
0000-0002-2785-4781

4th Abbas Khosravi
IISRI
Deakin University
Geelong, Australia
https://orcid.org/ 0000-0001-6927-0744

5th Saeid Nahavandi
IISRI
Deakin University
Geelong, Australia
https://orcid.org/ 50000-0002-0360-5270

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***Abstract*—Industry 5.0 is here, and human interaction experts claim that in the process of augmenting a high production/manufacturing workplace, a safety critical situation is created with the introduction of ”Cobots”. A Multi-Agent Safety System (MASS) is presented as a solution in this paper which uses commercial, wearable technologies with high data sharing acceptance rates such as the Apple watch to collect and share real time ECG signals with the Cobot. Principal Component Analysis (PCA) is selected as a dimension reduction tool because it is well established and meets the requirements for reliability in the development of a human-centric, safety system. Five Machine Learning (ML) classifiers (KNN, NB, RF, DT and GBM) are used with binary classification to predict whether the human is Distracted (Event 1) or Not Distracted (Event 0) to determine if this will pose a safety risk to the Human Robot Collaboration (HRC) System. Decision Tree (DT) classifier with 4 Principal Components (PCs) is evaluated at 98% Accuracy and 99%AUC and is the recommended model for future development of the MASS. A road map is also presented to ensure the longevity of MASS while signifying the inclusion of real time data which can close the demographic data gap and help to improve the privacy, efficiency and contextual reliability of the MASS model in the Industry 5.0 workplace.**

***Index Terms*—Industry 5.0, Human Robot Interaction, Human Robot Collaboration, Machine Learning, Principal Component Analysis**

I. Introduction

While the concept of humans and AI-Centric robots working together to achieve a common goal is found at the centre of many successful science fiction franchises. Experts believe that this partnership may soon become a reality in the next fifth industrial revolution [1] known as Industry 5.0. The focus of Industry 5.0 requires humans to collaborate with autonomous robots (contextually known as ”Cobots”) to achieve a mutual, occupational goal often in a safety critical environment i.e assembly line, logistics, military/war-zone etc.

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The prospect of this new industrial revolution has birthed new areas of research, development and application of technologies including Human Robot Interaction (HRI), Human Robot Collaboration (HRC) [2] and the Human-Machine Collective Intelligence (HMCI) [3]to study and mitigate any foreseeable impacts this may have on workplace health and safety, staff retention/well being and reduction of safety issues.Ann

The Cobot will have a primary function to perform an occupational task, but to become truly collaborative as a colleague, additional requirements are demanded from the system. Secondary responsibilities include ”mindful human interaction and liability, for health and danger” [1] and ”support for psychological well-being by facilitating social behaviour” [4]. According to experts surveyed on the topic of the emergence of human -level Artificial General Intelligence (AGI), 90% expected this to be achieved around the year 2075 [5]. Unfortunately, this is much too far off to enable any human-level decision making by a Cobot which can guarantee something as critical as human safety - as Industry 5.0 built around the ”additive technologies” offered by the

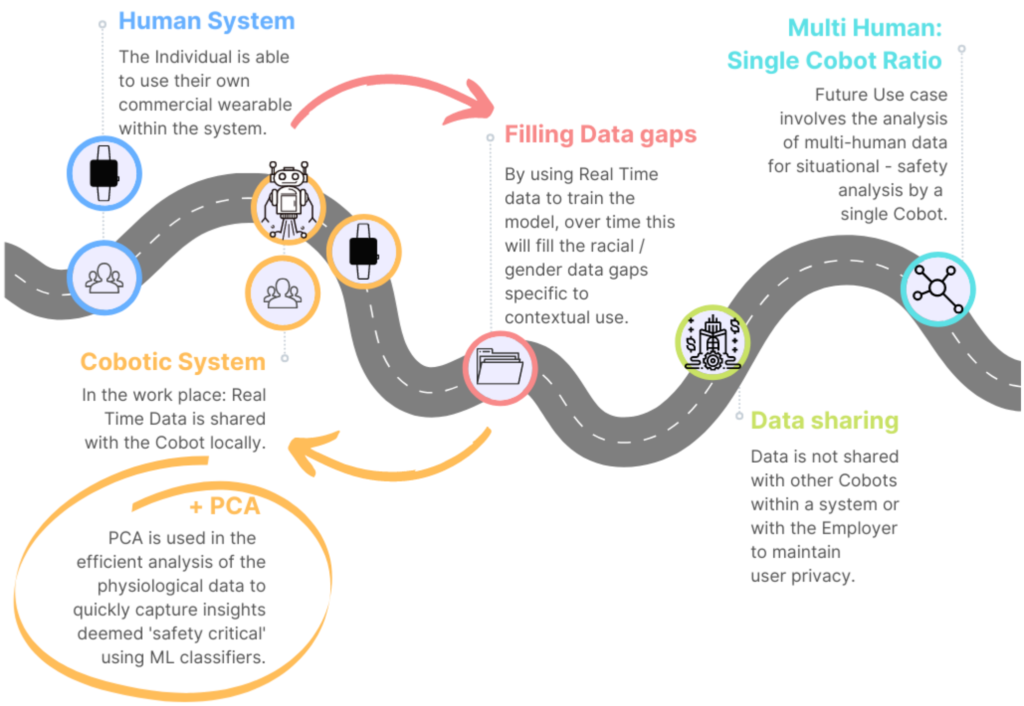

Fig. 1. The Road Map highlights the use case for the Multi-Agent Safety System (MASS) presented in this paper and more in detail in Fig. 2 which implicitly shares physiological data between Human and Cobot using PCA pre-processing and ML classification of physiological data between Human and Cobot to enable safe Human Robot Collaboration within the Industry 5.0 Enterprise Architecture.

newly built 5G network is already here [6].

Within the focus of safety critical environments, humans and robots are already working side by side. Research in these environments offer much opportunity for enhancement in human – machine interaction and optimisation. The study of human disasters and averted accidents in human space-flight [7], which also involve humans collaborating alongside autonomous systems, highlights the importance of human intuition [1] in the avoidance of unsafe situations.

Research into assembly- line workers revealed that repetitive tasks, urgency and resulting negative issues were reported as ”negative work attributes”. Positive attributes include minimisation of work interruptions and increased physical and psychological well being in the workplace [4]. With amendments to the workplace reported as producing an impact on the ”dimensions of the human experience, including motivation, satisfaction, fatigue, and cognitive demand” of the human [4].

Solutions pertaining to safety around HRC and HRI explored in academic literature include image recognition and rotor camera systems [1], hybrid control schemes of Cobotic autonomy which adjust based off the human skill level [8]. A study on Electroencephalogram (EEG) signals which were used to create a human- swarm interaction which adapts to the correlation between task difficulty increase to human performance decrements [9] is particularly relevant to the research presented in this paper. Psycho-physiological signals are used in both papers to classify psycho-motor efficiency using neural networks and support vector machine [9]. Another study [10] attempts to solve this problem by proposing a decision making AI system based off the information processing displayed by intelligence analysts. Controversially, the use of AI to augment human intelligence using reinforcement learning has also been explored in a bid to avoid training AI to “imitate flawed human traits” and instead training the human [11].

As part of the Enterprise Architecture (EA) Industry 5.0 Architecture, it will be essential to use ”multi-agent technologies which allow solving problems that are difficult to solve with the help of classical mathematical methods.” [12]. Wiring the human brain using psycho-physiological signals with the machine will enable a unified, collaboration which is critical for a human-centric system to safety management in Industry 5.0 [13].

Under this definition a Multi- Agent Safety System (MASS) is presented in this paper which incorporates intelligence in the form of applied mathematical methods Principal Component Analysis (PCA) and Machine Learning (ML)) to develop a system which interacts with the human at their cognitive level while modifying autonomy and proximity to ensure safety as a paramount while meeting occupational goals within the workplace. This implementation of interaction enables the system to become ”emergent intelligence”. In addition to the application of this system, we recognise

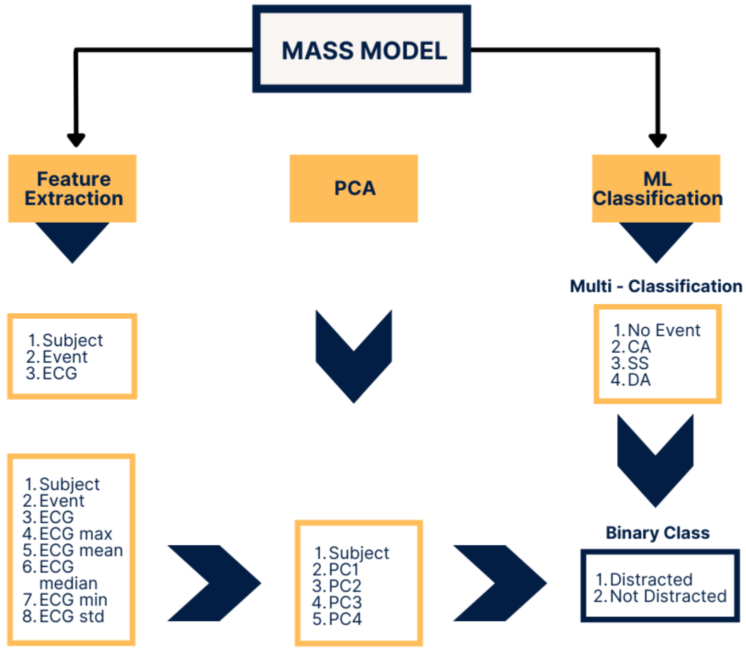

Fig. 2. The Methodology for the MASS model is presented here which will operate locally within the cobot to utilise data which is being shared implicitly by the Human collaborator. A conservative approach has been taken to extract additional features from the ECG and then utilise PCA to reduce the dimensionality without loss of information. Additionally, multi classification has been converted to a binary approach to achieve the goals of the safety system in the most efficient way.

latency of data transfer and recommend that any safety related task should be processed by the Cobot locally [13] using the system proposed here.

In this paper we test and demonstrate the efficiency of PCA analysis for the development of an human-centric system as part of Industry 5.0. We propose the use of a commercial, wearable technology such as a version of the Apple Watch which can support real time collection of continuous ECG for “low intelligence”, real time, data streaming [1]. The goal of this system is to share human psycho-physiological data in the form of ECG signals with the Cobot for faster, local processing and analysis to enable the system to understand human situational awareness. The Electrocardiogram (ECG) data will be used by the Cobot to gain awareness of the levels of human cognitive vigilance to undermine any safety implications of Cobotic presence in the workplace contributing to the increased chance of accidents. The psycho-physiological data collected in simulation used in this paper is reflective of a human working alongside an autonomous autopilot system where they are similar to Cobots ”performing repetitive tasks” [2].

PCA is used during pre-processing to reduce the dimensionality of the large, naturally occurring, ”non stationary” signals [14] such as ECG signals. The data will then be analysed by the Cobot using out of the box ML classifiers to determine organic and dynamic cognitive states of it’s human collaborator. While PCA has been labelled as an ”obsolete and displaced” [15] method, we argue the use of PCA is largely contextual. The Industry 5.0 - MASS proposed in this paper has been developed to meet a safety requirement as identified in semantic Industry 5.0 literature. Due to this critical nature safety PCA is employed as opposed to other data - reduction methods as it is essential to incorporate only well established and reliable methods [16] in the development of this system.

As researchers developing technology for use in the real world, we endeavour to improve conditions for workers who provide essential services in high demand, safety critical workplaces - and one day alongside autonomous Cobots. The authors would like to acknowledge the ”high risk between production quotas and injury/illness” as seen in logistical/assemblies such as Amazon [17]. With a disproportionate amount of people of colour working these jobs to provide for their families at the resignation of their own well being. While the data set used to develop the Minimum Viable Prototype (MVP) of MASS in this paper, is not currently reflective of this population. The authors have devised a road map shown in Fig. 1 in which Cobots can be built to fill this ”racial data gap” [18] through the reciprocation of a more relevant data set which can be achieved using the MASS system. The longevity of this significant, high-level purpose to fill the ”data gap” is supported by the real-time streaming of contextual data which will be collected with the end user in the occupational setting as represented in Fig. 1.

TABLE I
ACCURACY AND AUC OF THE CLASSIFIERS AFTER 10 RUNS.

Classifier	Accuracy	AUC	ACC w/PCA	AUC w/PCA
RF	0.90 ± 0.0	0.82 ± 0.0	0.77 ± 0.0	0.89 ± 0.0
GBM	0.89 ± 0.0	0.61 ± 0.01	0.61 ± 0.0	0.89 ± 0.0
NB	0.88 ± 0.0	0.55 ± 0.0	0.56 ± 0.0	0.88 ± 0.0
KNN	**0.96** ± 0.0	**0.95** ± 0.0	**0.97** ± 0.0	**0.98** ± 0.0
DT	**0.98** ± 0.0	**0.97** ± 0.0	**0.98** ± 0.0	**0.99** ± 0.0

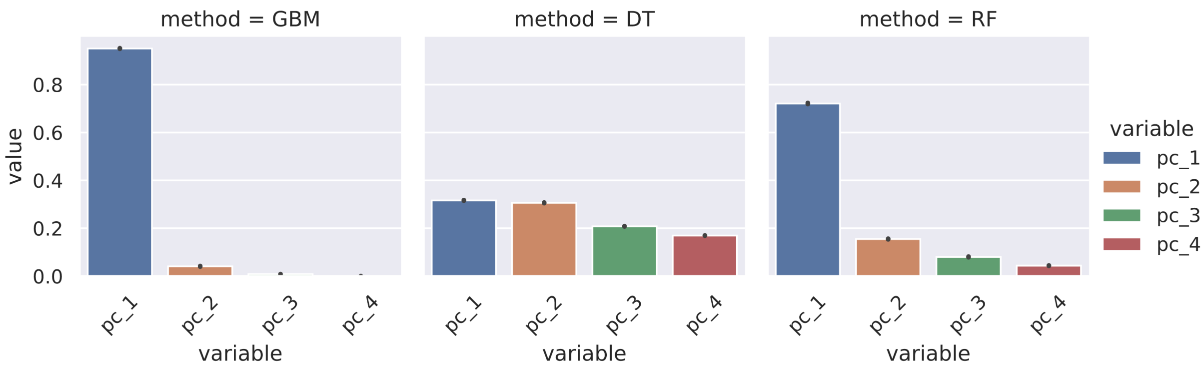

Fig. 3. The Variable Importance function is used to analyse the the importance of PCs used in each of the models GBM, DT and RF as to which PC's were important in the predictions being made. This is useful to determine the number of PCs which are actually useful for the prediction of the model which can impact decisions made on PC selection during pre-processing.

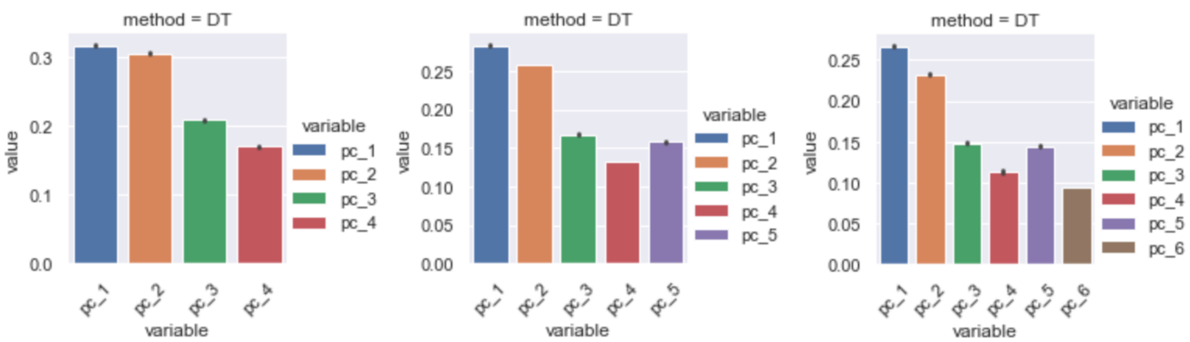

Fig. 4. A total of 6 principal components generated for Decision Tree to determine the optimal number of PCs to train DT classifier

II. METHODOLOGIES

The data set [19] used in this paper contains ECG signals collected in a Line Oriented Flight Simulator (LOFT) where pilots experienced simulations designed to illicit variations in adverse -alertness states of subjects. The original data set consisted of ECG, EEG, GSR and Respiration Rate (RR). However, for want of a commercial wearable in our system to manage the limitation of privacy and employer overheads, ECG is selected as it is already a data point which can readily be extracted from this technology today.

The subjects in the data set were occupationally trained pilots and to collect baseline measures they were exposed to controlled stimuli to generate physiological responses which correspond to baseline/no-event (Event 0), Surprise Startle (SS)(Event 1), Channelised Attention (CA) (Event 2) and Diverted Attention (DA)(Event 5). Similarly, most specialised Industry 5.0 occupations also require training and this repetitive exposure can cause data to exhibit patterns of "over-fitting". In the preceding research, a binary classification method was employed [7] to solve for this challenge.

The MASS (Fig. 2) enables the Cobot to use binary classification to efficiently predict the awareness/distraction states of the human using ECG signals to manage safety.

The very first step in preparing the data involved feature extraction in the pre-processing stage into a new data set which included the raw ECG signal, ECG_max, ECG_mean, ECG_median, ECG_min and ECG_std along with subject and event. PCA is then applied to reduce the feature extraction data set into 4 Principal Components (PCs) and in this method the dimensionality of the data is reduced from 8 to 6 columns without loss of information. The selection of 4 PCs for the creation of this new data set is done so conservatively as the context of use is for a safety system. The best performing classifier was then chosen to further experiment with optimal PC selection which was arrived at using a trial and test method so as to not compromise

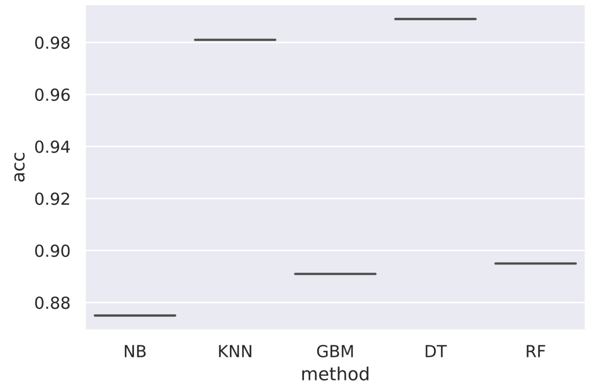

Fig. 5. Accuracy plot shows KNN and DT indicating very stable performances along with the other three classifiers.

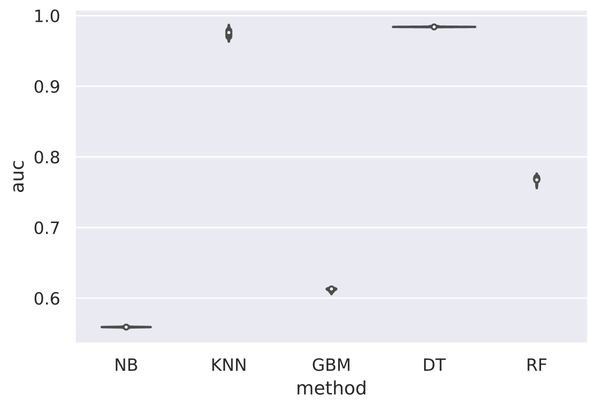

Fig. 6. AUC plot is a better determinant because it shows variation in performances and reveals weaker performance of models with KNN and DT continuing to perform strong.

the performance of Accuracy (ACC) and Area Under Curve metrics(AUC) this is further discussed in the results section.

The PCA data set was split into 80% to train the model and 20% to test the model. Five classifiers which included K-Nearest Neighbour (KNN), Decision Tree (DT), Random forest (RF), Gradient Boosting (GBM), Naïve Bayes classifier (NB) were selected to classify the data.

The model uses a binary classification method to predict whether the human is experiencing a Distracted state (Event 1) by combining Event 1(SS), Event 2(CA) and Event 5(DA) and Not Distracted (Event 0). Not Distracted state (Event 0) accounted for 90% of the data and displays a pattern of over-fitting. This data is highly contextual to occupational environments and it will be essential for real time data to be used to train a Cobot MASS models as highlighted in the road map in Fig. 1.

Comparisons were made with work which was previously completed [7] where PCA was not included in the model to determine whether the performance of the models could be improved for efficiency without compensating performance for the purposes of local Cobot processing for a MASS model.

III. Results

ECG results for Accuracy (ACC) and Area Under the Curve (AUC) were compared between two processes one which included 4 PCs and one without PCA [7] using 5 out of the box ML classifiers: Decision Tree (DT), Random Forest (RF), Gradient Boosting Machine (GBM), K- nearest neighbour (KNN), and Naive Bayes (NB). The results for the comparison of performance between the classifiers between the two processes of PCA vs. without PCA for ACC and AUC are presented in Table I.

For both processes (with and without PCA), DT is noted to be the best performing classifier for use with signals such as the multi channel ECG signals used in this paper. Regardless of PCA application, DT produces results of 98 % for Accuracy and for AUC an improvement of 2% can be seen with PCA and no errors. Minor improvements can also be seen for KNN with a 1% improvement in ACC with PCA application and 3% improvement in AUC. Further experimentation with DT and the optimal PC selection is shown in Fig 4 and Table II with the conclusion that 4PCs were in fact the optimal selection for this model.

However, for RF, GBM and NB significant decrements in accuracy are recorded combined with significant improvements for AUC. Due to the instability demonstrated by these models in these results they would not be recommended for use with this type of data.

Variable importance was available for three of these classifiers GBM, DT and RF and in Fig. 3 we can see that for GBM and RF - Principal Component 1 (PC1) contained the most amount of information used to train the model. Due to DT's superior performance for ACC and AUC it is worth nothing that all 4 PC's were useful in the predictions for this model. The limitation of this research is that KNN which was the second best performing model does not offer variable importance mapping and would have been an interesting comparison. Fig. 5 and Fig. 6 showcase that the performance of all classifiers are relatively stable with DT demonstrating best performance overall.

IV. Discussion and Conclusion

Ethically, there are elements of privacy and data sharing which come into question when developing and proposing a bold, yet novel system, such as the MASS model which is presented in this paper. However, the authors note the changing attitudes in data privacy-led by value provided to the user in sharing with corporations in contexts such as as Facebook, the emergence of the Metaverse and also the Apple ecosystem which is used as part of MASS model. Similar to an ergonomic chair in the office, the optimisation of occupational work-spaces with Cobots will be in the best interest of the human, and sharing the data required will enable calibration and added value of comfort for the human collaborator.

There is a possibility of a Cobot misinterpreting physiological readings from those living with mental illness, or an intellectual disability and this is a limitation which will

TABLE II
PCA ANALYSIS TO DETERMINE OPTIMAL NUMBER OF COMPONENTS FOR THE BEST PERFORMING CLASSIFIER - DECISION TREE (DT).

No. of PCs	4	5	6
Accuracy	**0.98** $\pm$ 0.0	0.99 $\pm$ 0.0	0.99 $\pm$ 0.0
AUC	**0.99** $\pm$ 0.0	0.98 $\pm$ 0.0	0.98 $\pm$ 0.0

be explored in depth in a future work. As reported earlier, corporate models such as Amazon have in place non-human performance evaluation and termination in place which is an area which needs further academic discussion. It is hopeful that the development of cybernetic systems such as MASS can integrate with, and augment the abilities of humans and enable a safer, personalised workplace where they can both collaborate effectively on tasks which benefit the greater good of humanity. A Multi-Agent Safety System (MASS) is presented in this paper to fill the gap for a secondary, safety management feature for the Cobots which will work alongside humans as a part of the Industry 5.0 EA. A technology road map is presented for this system which highlights how data will be sourced for real time analysis using a commercial wearable such as the Apple watch. PCA is proposed as a method to supplement out of the box ML classifiers as part of an MVP to improve efficiency of the MASS model which predicts any Distraction(Event 1) states of the human which may negatively impact their safety while working alongside the Cobot in the workplace.

The results presented in this paper evaluate a binary classification approach in conjunction with PCA to develop a ML model which predicts lapses in alertness using ECG signals. High performance metrics for ACC and AUC scoring are reported for the DT classifier. While the accuracy is stable across all models, the AUC score reveals weaker performing models and this is accentuated with the addition of PCA to the process. The PCA results are then compared with the performance of models without the use of PCA from a preceding research [7]. Based off both these results we recommend PCA as a valuable method, and when used with the DT classifier can provide optimum results in the development of a MASS model. As the road map suggests in Fig. 1 the model presented in this paper is only an MVP to demonstrate a concept, and it will be essential that real time data is collected for the successful implementation of the MASS model in an Industry 5.0 workplace.

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