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DESIGN AND EVALUATION OF QUALITY ASSURANCE-BASED INTERACTIVE MACHINE LEARNING MODEL

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ABSTRACT

Some complex task can be difficult to fully understand or represent or there may even be few data available about them thereby making it difficult to solve with classical machine learning approaches. Hence, Interactive Machine Learning (iML), an approach where humans are used to complement machines. However, existing interactive machine learning approaches have not sufficiently considered quality assurance of the human feedback in the interaction cycle to guaranty improved performance of the model. Interactive machine learning systems take on data for updates without checking the quality of the update data. This is capable of misleading a machine learning model if wrong, noisy or malicious data are used to update the model. Therefore, this paper proposes a quality assurance-based interactive machine learning model that is able to evaluate the quality of the feedback obtained from the human in the iterative feedback loop before passing such feedback to the learning model to update its knowledge about the problem. Existing literatures and concepts on interactive machine learning were reviewed. Also explored are areas where interactive machine learning approach has resulted in faster, less expensive model training process than the classical Machine Learning, especially when applied on rare and complex problems. Questionnaire method was used to conduct a survey that evaluates the usability and understandability of the proposed quality assurance-based interactive machine learning model using the Cognitive Walkthrough Strategy. The result gave a rating of 4.2 out of 5 for the usability of proposed model. This approach will increase the acceptability of the interactive machine learning model and the credibility of its predictions.

Keywords: *Evaluation, Human-in-the-loop, Interactive Machine Learning, Machine Learning*

1. INTRODUCTION

Machine Learning is a field of study curled out of artificial intelligence and traditional statistics and it looks at turning empirical data into usable models using computational algorithms[1]. It enable systems to learn, automatically, from observations and improve from their experiences without being programmed explicitly[2]. Machine learning involves developing programs that have the ability to access data and learn from it themselves[3]. Machine learning techniques can be categorised into Supervised, Unsupervised, Semi-supervised, Reinforcement learning techniques[4,5].

Machine learning (ML) promises people from all walks of life solutions and also provides data-driven insights. However, only a few are skilled with the ability to craft these solutions. Recent researches are creating interactive tools that are usable by non-ML experts, accessible and easy[6]. Interactive Machine Learning (iML) approach was developed to circumvent the shortcomings of other approaches for generating Machine learning models like Classical Machine Learning (cML) and Automated Machine Learning (aML).

Classical Machine Learning is one in which a human expert or data scientist is involved in the process of model generation and is difficult for non-programmers to use. The human expert is involved in identifying and selecting promising features from the dataset to create classifiers[7]. Its training is performed once and can be slow, resource-intensive, time-consuming (espaecially if features are many) and offline, hence the need for features to be carefully and correctly selected. It optimises model classification at the detriment of time of training, however, it enables a classifier to run quickly at real-time[8].

Automated machine learning (AutoML) select, compose and parameterise machine learning models automatically with the aim of achieving optimum output on a given dataset and/or task [9]. It is the process of automating machine learning model development[10].

Interactive machine learning is built on the “human-in-the-loop” approach. It allows iterative interactions between the classifier and the user towards defining and optimising a model[11].

This machine learning approach increases the level of users’ trust of Machine Learning systems which are largely considered as “black box” and sometimes performs not so good for the purposes intended[12], by bringing the user to the heart of the interaction with the machine learning system[13]. The goal is to leverage human beings to get good data in building our model[14].

The data may not be too large, but very good data - enough to build a highly effective model, as interactive machine learning approaches are effective in solving problems that have complex/scarce data sets. It also enable explainable-AI and ‘retraceability’ – these are important in some domains like the medical domain[15].

There are some complex machine learning problems with few labeled data available making it more complex for machines to solve. However, these problems are somewhat simple for humans to solve, for example, problems involving functional extrapolation. Other ML approaches are not as effective on tasks like function extrapolation problems whereas they are to a certain extent simple for humans to solve[16]. Another example is how does a little child easily differentiate between a dog and a cat without having to consume tons of data? So the question “how do humans get so much from so little data” was asked by Josh Tenenbaum[17]. This brought about the idea of humans being used to provide labels or feedback during model building and correcting any wrongly classified observation in the feedback loop making the process interactive, fast and requiring less amount of data to work with. However, this can result in a declining performance if the feedback or data provided to the model by the user are anomalous, invalid, fictitious or of low quality (18,19). Hence, the need to verify the validity (or ‘goodness’) of the input and ensure that only valid and high quality feedbacks are used in updating the model (12).

Ensuring that the data used for decision making or training/improving a learning model has integrity, accuracy, not abnormal and of high quality is still a challenging task and as well very relevant in many high-precision, safety-critical domains for example in dendrometer sensor networks monitoring in precision agriculture, fraud detection, intrusion detection et cetera (20). High quality of a data is what guarantees its effectiveness, value and the quality the resultant model learning from it, while poor data quality will lead to serious decision making mistakes (21).

This paper is structured as follows: Section 2 contains literature review. Section 3 describes the quality assurance-based model. Section 4 highlights the evaluation of the model, while section 5 concludes the paper.

2. LITERATURE REVIEW

2.1 Interactive Machine Learning Model

An iML system consist of an automated learning component and a user interaction interface. A human provides iterative feedback to the learning algorithm by interacting with the automated components through its user interface. This feedback may be from the system, inferred from user behavior/interactions or explicit[18]. The feedback is directly passed to the learning system to update the underlying machine learning model. Although at this point, the quality of the data point being used to train the model may not be assessed.

2.2 Foundational Concepts of iML

Humans-in-the-loop algorithms are the foundations of interactive machine learning. Human-in-the-Loop Algorithm is an emerging area of research in Artificial Intelligence where algorithms and humans interact to solve a problem. It involves leveraging on human intelligence to complement machine intelligence in the process of model creation[27]. This concept is aimed at improving system performance[22]. Correct predictions using these algorithms does not only depend on the machine algorithm, but also on the human, (otherwise called oracle or teacher) providing the feedback[28].

Interactive machine learning intersects and picks features from supervised learning, active learning and reinforcement learning techniques and in some cases online learning algorithms [11,14].

2.2.1 Supervised Learning

This is a type of learning using examples or observations that have labels [21,29]. It is a learning that learns a function that maps an input, based on sample input-output pairs, to an output.

2.2.2 Active Learning

It is the subset of supervised learning wherein a learning system can interactively query the teacher (or oracle) to provide labels to observations[30]. The algorithm selects the most valuable next example to be labeled, from a set of unlabeled examples.

2.2.3 Reinforcement Learning

It addresses sequential decision problem where the agent has limited feedback from the environment[30,31]. It is a type of learning where the agent uses penalty and rewards to train a system. The learning system learns within an interactive environment and for each action is performs, it receives rewards or penalties for performing correctly or incorrectly[32].

2.2.4 Online Learning

When the training data may not be available in batch, that is all at once, say due to limitation in memory size or due to an inherent nature of the problem, but is available in sequential order, online learning algorithms are able to work with this continuous flow data [14].

2.3 Evaluating iML Systems

Interactive machine learning systems adapt to and learn from humans, and humans also adapt to the system and receive feedback from the system, hence making the evaluation of iML systems an uneasy work. It is difficult to get a good understanding of the subtle mechanisms of co-adaptation and co-operation. Hence, evaluations and methodically correct experiments are time-consuming, difficult and may even be impossible to reproduce, simply because individual human agents are individually subjective[33].

However, it is suggested that coupling ‘algorithmic-centered analysis’ with ‘human-centered evaluation’ can help understand the system’s computational behaviour; and effectiveness and utility of the application for end-users respectively[18].

2.4 Application Areas of iML

2.4.1 Health Informatics

Interactive Machine Learning is suitably applicable in health informatics because of its ability to produce better results than aML and cML when provided a complex problem with few data or even rare events[34]. It can be helpful when applied to solving computational hard problems like k-anonymisation, protein folding, subspace clustering of health data when human expertise and feedback in the learning process can help reduce the complexity of what would have been an NP-hard problem. Clustering, for example, is an ML task that involves identifying homogenous groups of data objects in a plane. Clustering has numerous application in -omics where, e.g. there can be large gene expression data sets with high-dimensionality. These datasets, unfortunately, have a fuzzy underlying structure and cluster identification would generally require

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expert (human) knowledge about geometry and cluster number[33].

2.4.2 Guided Visual Exploration

This involves a dynamic and unpredictable procedure of finding interesting patterns in a search space. It is unpredictable because there is no fore knowledge of the user's goal and it focuses on testing, organisation, developing concepts, definition of assumptions and finding patterns. However, finding these interesting patterns and exploring a large search space can be tedious as mostly, it is a multidimensional dataset. Multidimensional scaling or principal component analysis (PCA) can be used for dimensionality reduction, but they can be difficult to understand, hence an iML approach that combines stochastic optimisation by means of interactive evolutional algorithm (IEA) with visual analytics is used to guide user to interesting patterns or projections, where interestingness is identified subjective human assessment (explicit) and automatic indicators (implicit)[18].

2.4.3 Human-Computer Interaction (HCI)

HCI is an area which focuses on designing computing technologies that enable interactions between computers and human (users). The iterative nature, directness and speed involved in iML makes it usable for supporting rapid prototyping for interaction design[35]. Interactive machine learning have been applied in this area in six workshops with people with learning and physical disabilities, in the design and customisation of gesturally controlled musical interfaces[36]. Also, iML has been applied in the creation of Perceptual User Interface (PUI)[8].

2.4.4 Seed and Seedling Quality Classification (Agriculture)

The quality of seeds is very sensitive to post-harvest processes and environmental conditions, such as artificial drying, mechanical threshing and, and the achievement of high yield in soybean farming depends on the efficient establishment of soybean plants that require the use of high-quality seeds. It is therefore especially necessary to identify low-quality seed lots and, often time, the identification is done by chemical methods that are harmful and visual inspection of seed lots that are subjective, unreliable and consumes a lot of time. In order to analyse the quality of agricultural products, especially seeds, iML together with computer vision have been combined, to address many of the constraints faced by conventional visual seed inspection methods[37].

2.5 Research Issues in Interactive Machine Learning

The solutions suggested by Interactive Machine Learning systems are often inexplicable for end users. There is a need to understand how interaction with the model, impacts the user's level of trust of the model[11]. This is because the user is not able to access the feedback strategies, internal workings of algorithms that lead to system suggestions. It is difficult to resolve this "black-box" effect as there is a delicate balance between the richness of a transparent design and the simplicity of a more opaque one[12].

The assessment of Interactive Machine Learning systems is still a challenging task.. Current assessments tend to concentrate on single isolated components such as the interface's utility and the algorithm's robustness despite the multifaceted nature of Interactive Machine Learning systems[18]. The assessment of affective-cognitive states and behaviors of users should also be incorporated into such a standard, and also consider some factors – complexity, immediacy, robustness, deterministic and flexible interaction[11,18].

Because Interactive Machine Learning works well with few data and cases of rare nature, there are chances that Interactive Machine Learning may produce overfitting models as identified by[41]. Overfitting means a machine learning algorithm corresponds too closely to the training data and hence may not be able to generalise well with new data. Hence the problem of overfitting within interactive machine learning systems may be investigated[42].

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2.6 Future Trends

An area of possible progress is in the pervasiveness or generality of interactive learning systems in iML. At the moment, most of these systems are used in particular parts of the application and they expect a definite kind of interactions. But users are engaged in a much larger discussion in most applications that incorporates multiple tools and activities such as post-processing and data preparation [13]. It is also important to address the questions of how to help users (humans) during collaboration with big data and machine learning algorithms. Here, experts in Human Computer Interaction (HCI) and ML will need to collaborate in this research endeavor that has the potential of helping problem solving in the future and greatly[43].

3. THE QUALITY ASSURANCE-BASED iML MODEL

As against directly passing unassessed data points to the learning system, the quality assurance-based iML model (See Figure 1), ensures that the quality of the human's feedback is assessed before the manual correction is applied on the ML model being trained.

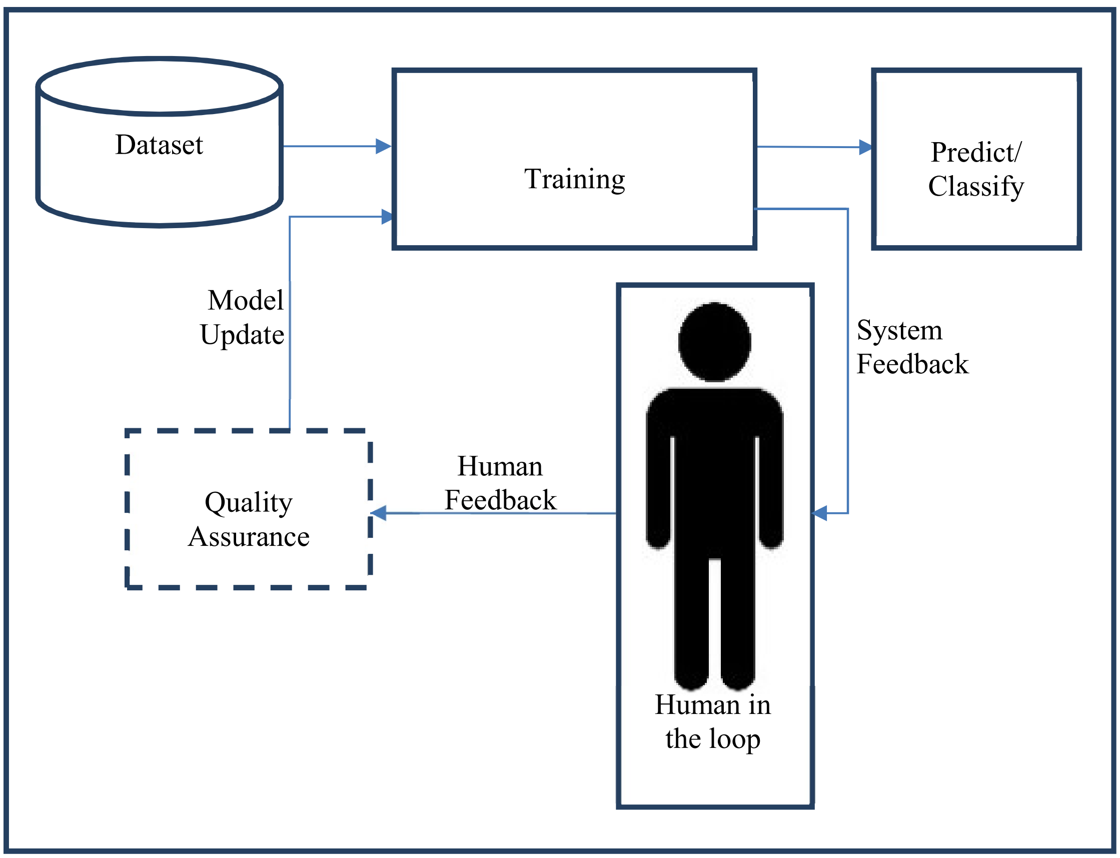

Figure 1: Quality Assurance-based Interactive Machine Learning Model (Adapted From [7], [8])

3.1 Description of the Quality Assurance-Based iML Model Components

Figure 1, quality assurance-based interactive machine learning model was adapted from [7], [8], and the components are described as follows:

3.1.1 Data

This is the training data upon which our machine learning model is being trained. The quality of a model's predictions is only as good as the quality of the (training) data supplied to it. Hence, if the training data is not good enough in terms of quality, it may result in low quality predictions or longer training time to get accurate predictions[19].

3.1.2 Training

Simply put, it is the determining (learning) of good values for the bias and weights from examples or training data. In iML, this process is an iterative one where the machine learning algorithm updates the prediction model according to the data and feedback given to it[20].

3.1.3 Predict/Classify

This is the process of using the trained model to determine the outcome variable for a new data observation. While prediction determines (predicts) continuous valued outcomes, classification involves predicting categorical class labels[21].

3.1.4 Feedback

Feedbacks are provided to potentially improve the system's performance [22], which could be human or system feedback. The human feedback is provided to correct model errors, by updating parameters of the model to adapt to changing data. The human feedback may be inferred or explicit[18]. The system feedback, beyond just showing outcome of the human-computer collaboration, provides information about the provenance of the system suggestion and the state of the ML algorithm[18].

3.1.5 Human-in-the-Loop

In iML, as against what is obtainable in classical machine learning, humans do not only pre-process data by selecting quality features. In actual sense while learning, humans directly interact with the learning algorithm[23]. Also, there might be more than one human interacting with the learning system, thereby enabling crowdsourcing[23].

3.1.6 Quality Assurance

The quality assurance component is responsible for evaluating the quality of the human feedback, otherwise known as human-centered evaluations, before the feedback is used to manually correct or effect the model[18]. However, a study of semantic interaction by [24] states that rather than focusing on synthesising information that are relevant to the task, an indicator for success in interactive machine learning systems is when the human forgets that he/she is feeding an algorithm. In other cases, it may require initially ranking the humans (or oracles) based on expertise on the application area of the iML system i.e. to know which of the oracles is likely to give "low-quality", or "high-quality" feedbacks, so that when a "low-expertise" oracle provides a fuzzy feedback, such feedback is represented to a "high-expertise" oracle before it can be applied on the learning model[25].

3.1.7 Model Update

This is the process of applying the evaluated or assessed feedback as a training data to the model in order to improve the performance of the learning system.

4. RESULTS OF EVALUATING THE iML MODEL

In evaluating the quality assurance-based interactive machine learning model, the Cognitive Walkthrough Strategy was employed, where a person or a group of persons (called evaluator(s)) inspect a system. It is task specific. In other words, by going through a set of tasks to assess its ease of learning, understandability and usability[38][39][40]. The survey was conducted using a questionnaire which had questions grouped under five (5) factors (Clarity, Ease of Use and Entry/Exit Control (UEE Control), Flow Control, Performance Expectation and Overall). Twenty (20) questionnaires were administered, but 18 respondents responded. These 18 responses were analysed and reported. The questions were five-point Likert-scaled (a type of psychometric response grading, where responses are based on level of the respondent's agreement with the stated fact. The scale is calibrated as 5, 4, 3, 2 and 1 representing Strongly Agree, Agree, Neutral, Disagree and Strongly Disagree respectively[38].

Figure 2 below shows individual respondent's rating of the proposed model based on data collected from the 18 respondents via questionnaire method.

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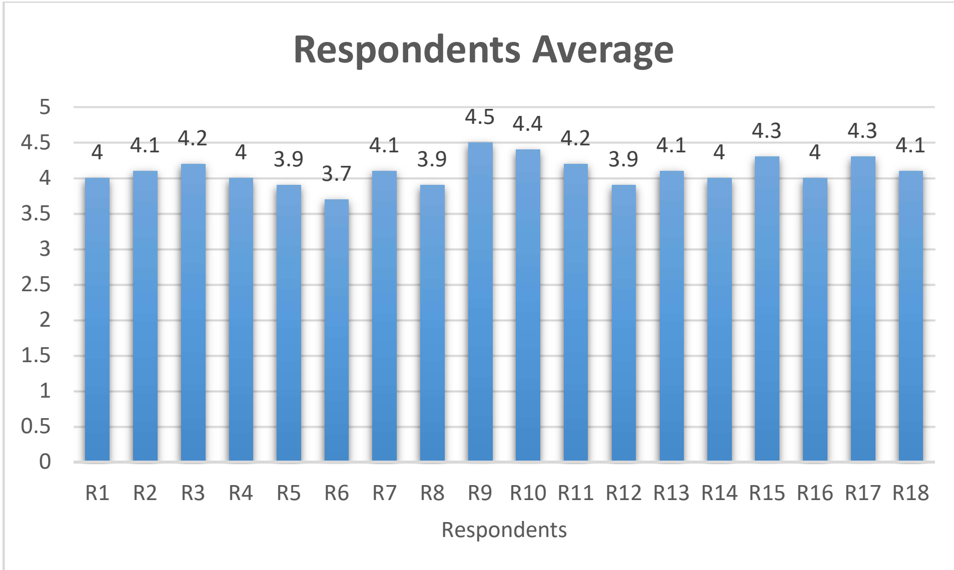

Figure 2: Quality Assurance-based iML rating by each respondent

From the analysis and as show in Figure 3 and Figure 4 below, it was found Clarity (4.31), Ease of Use and Entry/Exit Control (3.86), Flow Control (4.28), Performance Expectation (4.00) and Overall (4.03). The average score of the usability and understandability of the model is (4.09). And according to numerous studies about usability, systems can be graded as having a mean rating x of Very Bad (x=1), Bad (x=2), Average (x=3), Good (x=4) and Excellent (x=5). Therefore, going by this, it can be concluded that the quality assurance-based iML model has a "Good" usability and understandability rating.

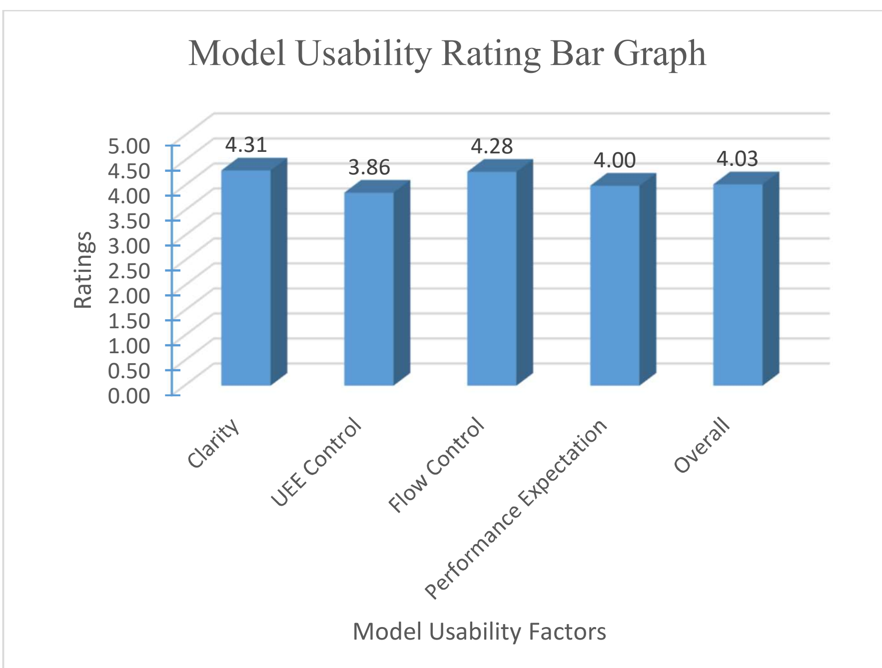

Figure 3: Users rating of the proposed model by usability factors

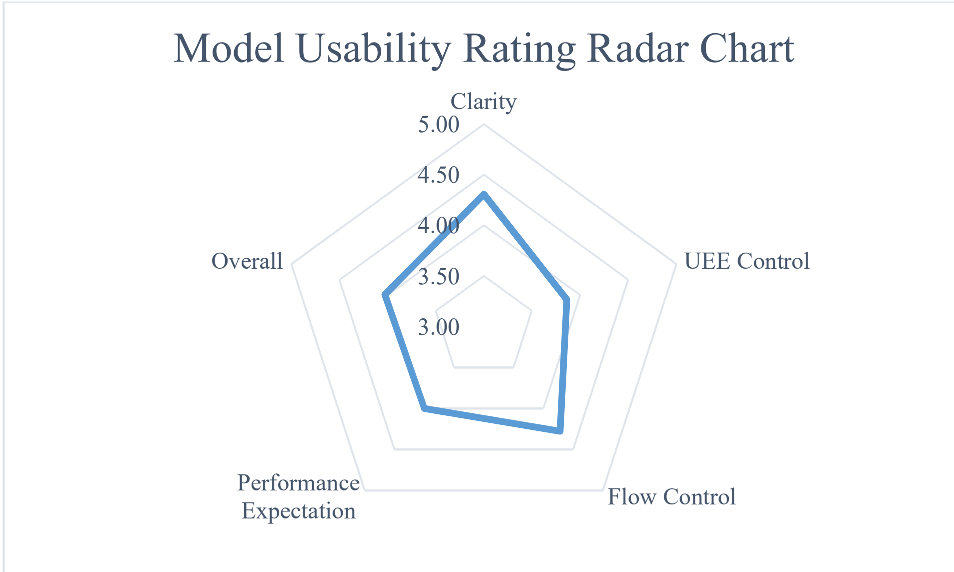

Figure 4: Radar chart of Model Usability Rating

5. CONTRIBUTION TO KNOWLEDGE

The contributions of this work to the body of knowledge are in two ways. First, it introduces a module into the interactive machine learning model which can be used to confirm quality of a data feedback before using same as an update. And secondly, it provides an evaluation of the usability and understandability of this newly developed model. This evaluation resulted in a "Good" rating of quality using the Likert scale.

6. CONCLUSION

Prior studies utilised machine learning tools in predictive systems [45,46]. This work is an overview of interactive machine learning with the aim of proposing a quality assurance-based interactive machine learning model. It was done by reviewing literatures and studying concepts to identify currents trends, application areas, research issues, practical applications and future trends in the area of interactive machine learning. From the reviews, Interactive Machine Learning is seen to be an advancement of machine learning in that it also turns empirical data into usable models using computational algorithms, but this time, with a human-in-the-loop (users or experts – not necessarily ML experts) thereby resulting in a faster, less expensive, interactive and iterative learning process resulting in a more customised model..

However, the quality assurance component of the iML model, identified and contributed in this work, seeks to evaluate the effectiveness of the human feedback before applying it as a correction to the learning model. This is to provide better performance on rare and complex problems and increase the acceptability of the model and the credibility of its predictions.

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