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Application of Machine Learning in Addressing Human Computer Interaction Challenges

Adimora, K.C and Aru, O.E
Department of Computer Engineering, College of Engineering and Engineering Technology,
Michael Okpara University of Agriculture Umudike, Umuahia Abia State, Nigeria
*Corresponding author's email: kyrimanjero@gmail.com

Abstract
Human-Computer Interaction (HCI) depends on data from multiple modalities such as audio, video, text, and many more as inputs. These signals have varying metric values and time scales that make it difficult for a human mental model to interact with computer systems effectively. This interaction hiccup has frustrated the manufacturers' design strategies in many aspects especially in the area of computers not being able to reason, learn or provide ideas on their own like humans in the course of interaction. Conventionally, a computer depends on the instructional code to operate and this has limited a computer from reasoning independently. In this paper, a machine learning (ML) technique was deployed to enable computers to operate and reason like humans at all times without adhering to the conventional approach of solely depending on the instructional code before it could perform a task. Several machine learning datasets were trained and tested in this study with performance evaluation metrics based on feature selection and confusion matrix that gave 99.09 percent accuracy in human-computer interaction. The research results revealed the effectiveness of the system in addressing observable hurdles in human-machine interaction.

Keywords: *Human computer interaction, Machine learning, Feature selection, Computers based technologies, Confusion matrix*

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1. Introduction

The issue of Human-Computer Interaction (HCI) among software engineers and the manufacturers of computer-based technologies is a great concern and would continue to be if no specific solution is proffered to address the outstanding challenges. Therefore, it becomes imperative to collapse the human-computer interaction limitations through the application of machine learning instead of adopting the conventional approach of the system design that never allows the machine to think, reason, and interact like humans. In this study, creating a system that will have the ability to think, reason, and interact seamlessly with humans using machine learning instead of the traditional approach is the identified knowledge gap. Grudin (1990) executed research in which he has argued that HCI had gone through a number of stages, and in the early days of computer systems, it moved from a focus on a dialogue between humans and computers to a focus on work settings. This early focus of usability research that was largely interested in low-level human-computer interaction issues progressed to a focus on tasks wherein a single user interacts with a desktop computer in a work setting (Norman,1990) and (Suchman, 1987). With the development and widespread use of computer network technologies, such as the Internet, a move towards a new digital world, characterized by network and social design, has come forward. As users increasingly reached out to each other through computer networks, and internet technologies, HCI became "socialized" (Wellman, 2001). Human-Computer Interaction (HCI) is the study of the design, evaluation, and implementation of interactive computing systems for human use and the major phenomena surrounding them. HCI consists of three parts the person, the computer, and the ways they work together which is mainly the concern of every researcher of human-machine interaction.

Human-Computer Interaction (HCI) was described as the point where the human can tell the computer what to do or a point where the computer displays the requested information. Human-Computer Interaction sometimes called Man-Machine Interaction or interfacing is a concept represented by the emergence of computer-based technologies. Gautam (2015) remarked that most sophisticated machines are worthless unless they can be used properly by men, through seamless human-machine interaction. In the interaction with a computer system, the human input is the data output by the computer and vice versa. Input in humans occurs mainly through the senses and output through the motor controls of the effectors. Vision, hearing, and touch are the most important senses in Human-Computer Interactions (HCI). The fingers, voice, eyes, head, and body position are the primary effectors (Dix *et al.,* 2005). Wang *et al.* (2021) conducted a bibliometric review on human-computer interaction in the field of hazard recognition from a practical perspective. Abadin *et al.* (2021) carried out research on brainwave stimuli diagnosis using binaural beat sound to pick up a person's sensitive information.

The mental model describes the users' perception of computer systems' behavior towards solving problems in the environment. The human-computer interfaces are designed to connect the users' mental models for easier and more efficient execution of work. Paluri (2020) focused on fidelity prototyping that incorporates the emotional intelligence of the users to develop a mental model that will improve human interaction with the computer interface. Holzinger *et al.* (2019) carried out a research study that demonstrated the effectiveness of interactive machine learning that enables humans to directly interact with a learning algorithm. Madhusudan *et al.* (2020) reviewed work on the intelligent human-computer interaction that described cognitive modeling and systems, intelligent usability and test system, and human-centered AI applications.

Ziefle (2010) executed research work that outlined the Scio-technical challenges of future human-computer interaction (HCI). Huang (2009) conducted research that explored the human-computer interaction challenges in the design applications of hardware and software for mobile devices. Xu *et al.* (2021) conducted a research study that differentiated non-AI computing systems from AI systems with respect to human-computer interaction and challenges. Florian *et al.* (2022) carried out research on the issue of a prototype system with respect to a common approach in human-computer interaction (HCI), usable privacy, and security. Fig. 1 described the feature selection process of the supervised learning algorithm.

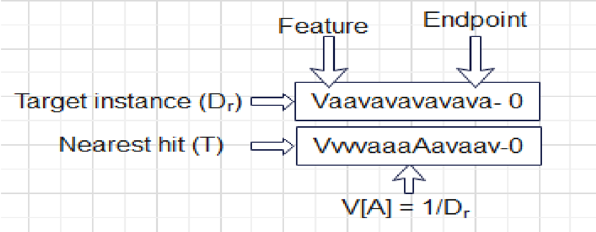

Fig. 1: Feature selection process by the supervised algorithm (Urbanowicz *et al.*, 2018)

The incorporation of users' emotional intelligence to develop a more user-like system for the best human-computer interaction was a great challenge and concern to software engineers. This has affected the feasibility of designing a computer mental model that will look the same as the mental model of the user (Erlich, 1996 cited in Srujan, 2020). Ziefle and Jakobs (2020) executed research that outlined the socio-technical challenge for future human computer interaction (HCI).

2. Materials and methods

The materials and methods used in the design and implementation of the new system in addressing the issue of privacy, security, and ethics in human-computer interaction are briefly discussed in this section. The machine learning approach that is based on feature selection is the adopted design method for implementing and reporting research findings. The research approach allows evolving integrated machine learning algorithms (Support Vector Machine, Linear Regression, and Decision Tree) to be able to enhance human-computer interaction compatibility. The study attempts to modify the traditional view of human-computer interaction (HCI) through the implementation of an intelligent system that facilitates the use of machine learning in addressing HCI's outstanding challenges. In this paper, a supervised algorithm that is based on the Genetic Algorithm, K-Mean, and Auto-encoder feature selections is deployed. Feature selection (FS) is a necessary step in the machine learning process and due to appropriate feature selection the machine learning (ML) model performance increases and the computational time of the model decrease (Meesad *et al.*, 2011). The pseudo-code of the supervised algorithm-based feature selection is given in Algorithm 1. The research dataset was got from the UCI machine learning repository of HCI. Dataset performance evaluation metrics are depicted in Tables 1, 2, 3, and 4 respectively.

Algorithm 1 Supervised learning feature selection (FS) algorithm pseudo code

Input: SL: Training data with labels feature, parameters required d: Training instances applied to updated data value V
Output: V: Data feature value → (fv)
1: n →Total instances used for training
2: d_t →Used trained feature data
3: $V[A]$ ← Updated data value analyzed and initialized to zero (0)
4: $C[A] \leftarrow 0$;
5: $\boldsymbol{for}\ j \leftarrow 1\ To\ n$ **do**
6: Select randomly 'Target' instance D_r
7: Determine (T, M)
8: Compute hit at target T and miss at target M
9: $\boldsymbol{for}\ i \leftarrow 1 To\ k$ **do**
10: $V[D] \leftarrow C[A] - \frac{dv}{dt}(T, M)/N$
11: $\boldsymbol{end\ for}$
12**:** $\boldsymbol{end\ for}$
13: **Return V;**

Where SL is the supervised learning, V is the updated data value, FV is the feature value, A is the analysed updated data, D_r is the randomized data, T is the target, M is the missed target, n is the total number of instances, N is the net data, and C[A] is challenged addressed. The individual ML algorithm classification performance is carried out using data set from the UCI ML repository. The performance of the new system is checked on full and on selected features sets selected by Genetic Algorithm, K-Mean, and Auto-encoder FS algorithms for prediction of seamless human-computer interaction. Also, the pseudo-code of the Linear Regression (LR) algorithm-based feature selection is given in Algorithm 2.

Algorithm 2: Linear regression feature selection (FS) algorithm pseudo code

Start
Generating classifiers:
$\boldsymbol{for}\ i = 1\ to\ n\ \boldsymbol{do}$
Randomly selected data d_i for training
Creating root node, R_i with d_i
Call DecisionTree (R_i)
$\boldsymbol{end\ for}$
DecisionTree (R):
$\boldsymbol{if}\ R$ having single class **then**
$\boldsymbol{return}$
$\boldsymbol{else}$
K% of splitting features in R is selected randomly
Feature selection (FS), with more information for splitting
Creating child nodes of r_i
$where, R_i$ contains r_i possible values $(R_i, \dots, r_i\ )$
$\boldsymbol{for}\ i = 1\ to\ n\ \boldsymbol{do}$
$Set\ content\ of\ R_i\ to\ d_i,$
$where\ d_i$ = all of the matching instances in R
$(FS)_i$
Call DecisionTree (R_i)
$\boldsymbol{end\ for}$
$\boldsymbol{end\ if}$
$\boldsymbol{end}$

Where K% is the split feature selection, R_i is the root node, r_i is the child node, d_i is the trained data, i is the initialized value, n is the total instance for training, and j is the allowable boundary condition for the total instance for training.

3. Results and discussion

3.1 Experimental results

In this section, we present details of our results findings based on the trained and tested datasets. Table 1 summarized the appropriate percentage of training parameter, training time, and testing accuracy that compares existing HCI to the proposed system.

Table 1: Functional comparison between existing and proposed system

	Training Parameter	**Training Time**	**Testing Accuracy**
Existing HCI	246 million	20 minutes	85%
Proposed HCI	6 million	8 minutes	99%

The number of parameters is significantly reduced in the proposed system compared with the existing HCI model. The number of training parameters processed in the proposed HCI is 6 million while the existing HCI requires 246 million parameters to be processed in the data training stage. The proposed HCI model has less percentage training parameter that drastically reduced the system computational cost. Training time reduces from 20 minutes to 8 minutes with a significant percentage reduction in time cost. The proposed system evaluation performance testing accuracy is 99% compared with 85% of the existing system. The ML different kernels, such as SVM, DT, and LR with hyper-parameters values of$\gamma = 1$, and$\beta = 0.0001$, is used in the experiment to effectively train the classifier as depicted in Table 2. The classification of SVM, DT, and LR on full features set and on selected features sets by Genetic Algorithm, feature selection algorithm has been tabulated in Table 2.

Table 2: Full and selected feature set classification from ML UCI dataset by Genetic Algorithm

Classifier	Parameters (γ, β)	Feature set	Spec.	F1-measure	C.A.	Acc. (%)
SVM	(1, 0.0001)	Full	94	96	Yes	96.03
SVM	(1, 0.0005)	Selected	97	99	Yes	99.01
DT	(1, 0.0001)	Full	96	97	Yes	97.05
DT	(1, 0.0005)	Selected	98	99	Yes	99.06
LR	(1, 0.0001)	Full	95	96	Yes	96.03
LR	(1, 0.0001)	Selected	98	99	Yes	99.01

Where Spec. denotes the specification, C.A. denotes challenge addressed, γ is the computer reasoning value, β is the human reasoning value, and Acc. is the accuracy of the new system in addressing the identified challenges. Also, the classification of SVM, DT, and LR on full features set and on selected features sets by K-Mean, and Auto-encoder, feature selection algorithm is depicted in Tables 3 and 4 respectively.

Table 3: Full and selected feature set classification from ML UCI dataset by K-Mean

Classifier	Parameters (γ, β)	Feature set	Spec.	F1-measure	C.A.	Acc. (%)
SVM	(1, 0.0001)	Full	95	97	Yes	97.05
SVM	(1, 0.0002)	Selected	98	99	Yes	99.03
DT	(1, 0.0001)	Full	96	96	Yes	96.05
DT	(1, 0.0003)	Selected	97	99	Yes	99.00
LR	(1, 0.0001)	Full	94	98	Yes	98.07
LR	(1, 0.0002)	Selected	98	99	Yes	99.06

Table 4: Full and selected feature set classification from ML UCI dataset by Auto-encoder

Classifier	Parameters (γ, β)	Feature set	Spec.	F1-measure	C.A.	Acc. (%)
SVM	(1, 0.0002)	Full	98	98	Yes	98.05
SVM	(1, 0.0005)	Selected	98	99	Yes	99.09
DT	(1, 0.0002)	Full	96	97	Yes	97.05
DT	(1, 0.0005)	Selected	98	99	Yes	99.04
LR	(1, 0.0002)	Full	97	98	Yes	98.02
LR	(1, 0.0005)	Selected	98	99	Yes	99.08

The system performance evaluation metrics have been used for training and testing datasets for accurate reasoning of the system to interact seamlessly with humans. The flowchart of the new system is depicted in Fig. 2. Fig. 2 described the model operations of the new system with the application of a support vector machine, linear regression, and decision tree algorithms of machine learning that are based on the Genetic Algorithm (GA), K-Mean, and Auto-encoder feature selection (FS). The UCI ML data set were split into two training set and a testing set which was first pre-processed with assumed reasoning parameters for computer (γ) and humans (β). The equality in two-party reasoning based on the available data is the positive prediction that the interaction challenge has been addressed. Table 5 is the comparison of results obtained from the trained and tested classifier and is illustrated in Fig. 3.

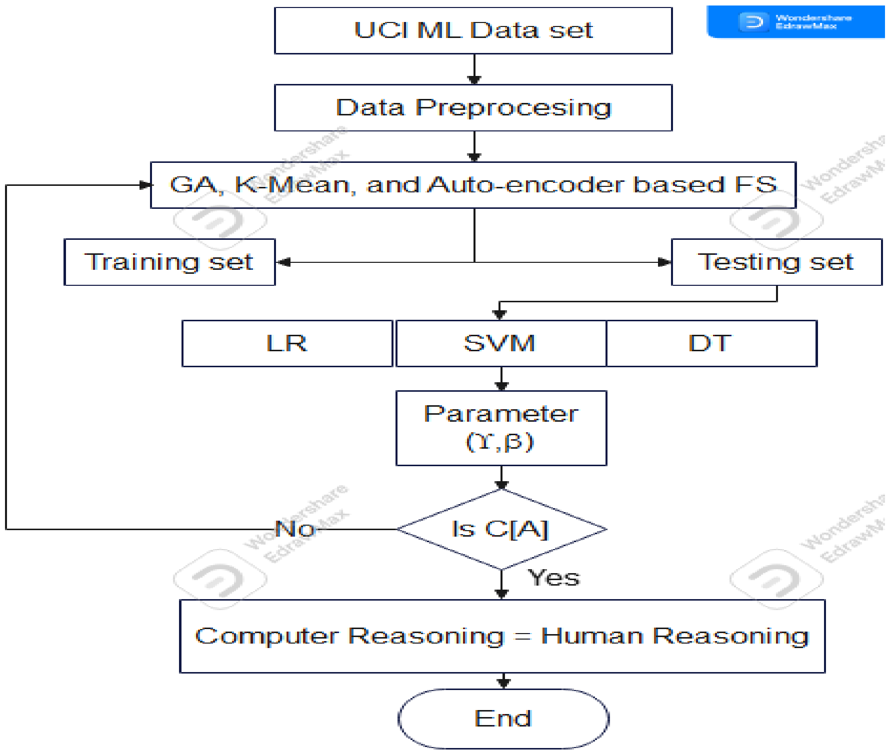

Fig. 2: Flowchart of the new system

Table 5: Classifier results comparison

SVM	LR	DT	Performance Evaluation metrics rule
2158	2045	2213	valid classification of trained and tested data
99.01	99.01	99.06	GA valid recognition rate (%)
99.03	99.06	99.00	K-Mean valid recognition rate (%)
99.09	99.08	99.09	Auto-encoder valid recognition rate (%)

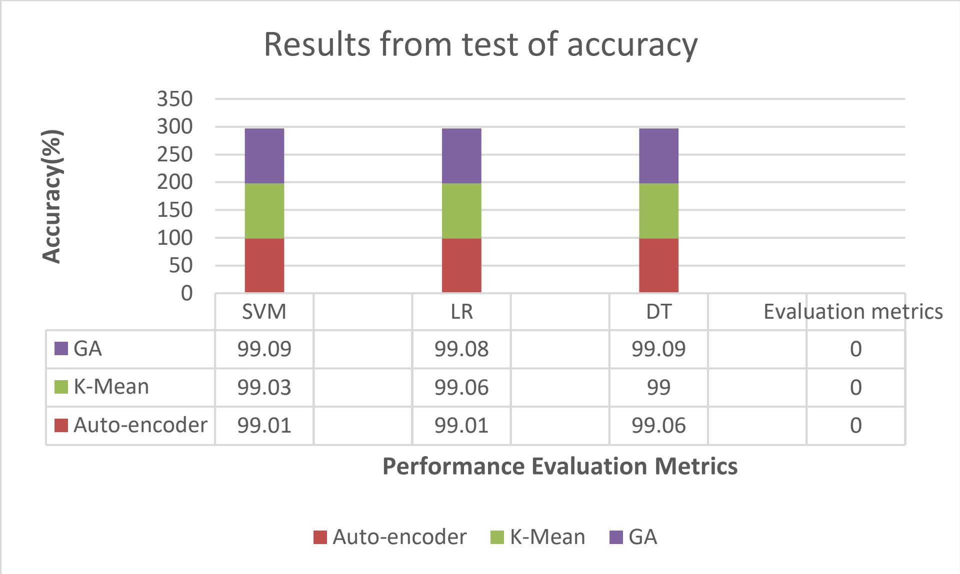

Fig. 3: Feature selection perfection evaluation metrics

Fig. 3 explained the accuracy of trained and tested data in support vector machine (SVM), linear regression (LR), and decision tree (DT). It also detailed the percentage of accuracy achieved in each of the feature selection algorithms. Under SVM the Genetic Algorithm (GA) data feature extraction accuracy is 99.09 %, K-mean accuracy is 99.03%, and Auto-encoder accuracy is 99.01%. Also, Under Linear Regression (LR) the GA accuracy is 99.08%, K-Mean accuracy is 99.06%, and Auto-encoder accuracy is 99.01%. Finally, under the DT the GA is 99.09%, K-mean is 99%, and Auto-encoder is 99.06%. In all excellent valid recognition, the rate was got. This showed that the issue of human-computer interaction has been addressed with an accuracy rate above 99%. In order to strengthen the result of the error rate being the accuracy, we employed a confusion matrix.

3.1 Confusion matrix

The error matrix helped us to visualize the performance of the classifier that addressed the issue of human-computer interaction observable in our computer-based technologies design. Table 6 shows the confusion matrix for computer reasoning (CR) and human reasoning (HR).

Table 6: Confusion matrix performance evaluation metrics

Actual Classes	**Predicted Classes**	
	Computer	Human
Computer	75	2
Human	1	81

This means that the classifier correctly predicted a computer in 75 cases and it wrongly predicted 2 computer instances as human. It correctly predicted 81 instances as human and 1 case had been wrongly predicted as a computer instead of a human. Therefore, the confusion matrix accuracy for the study is computed as follows:

$$Accuracy = \frac{QCP*classifier}{SP*classifier} \quad (1)$$

Where $QCP * classifier$ is the quotient of correct predictions made by a classifier and $SP * classifier$ is the sum of the predictions made by the classifier.

$$Accuracy = \frac{(75+81)}{(75+2+1+81)} = \frac{156}{159} = 0.9811$$

This means we have an accuracy of 98.11%. This is approximately the value of accuracy realized with the feature selection method. With such accuracy value, computers, and humans can interact seamlessly without the likelihood of interaction challenges.

4. Conclusion

The inability of the machine to reason along with humans for seamless interaction has been a great concern to computer-based technology manufacturers. In this study, we found out that the interaction limitation was due to the conventional approach of the system design. In order to address the identified human-computer interaction challenge machine learning that is based on the feature selection concept was deployed for dataset training and testing in evaluating metric rules for seamless interaction between human and computer systems. The valid recognition accuracy revealed a significant impact of the new system in addressing the human-computer interaction challenges. We recommend that future work should attempt to employ deep learning in assessing computer intrinsic reasoning and learning based on the available data.

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