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# Examining the Success of Information Gain, Pearson Correlation, and Symmetric Uncertainty Ranking Methods on 3D Hand Posture Data for Metaverse Systems

Cüneyt YÜCELBAŞ*[1], Şule YÜCELBAŞ[1]

## Abstract

Metaverse is a hardware and software interface space that can connect people's social lives as in the real-natural world and provide the feeling of being there at the maximum level. In order for metaverse systems to be efficient, many independent accessories have to work holistically. One of these accessories is wearable gloves called meta gloves and equipped with sensors. Thanks to it, an important stage of metaverse systems is completed with the detection of 3-dimensional (3D) hand postures. In this study, the success of Information Gain, Pearson's Correlation, and Symmetric Uncertainty ranking methods on 3D hand posture data for metaverse systems were investigated. For this purpose, various preprocessing was performed on the 3D data, and a dataset consisting of 15 features in total was created. The created dataset was ranked by 3 different methods mentioned and the features that the methods determined effectively were classified separately. Obtained results were interpreted with various statistical evaluation criteria. According to the experimental results obtained, it has been seen that the Symmetric Uncertainty ranking algorithm produces successful results for metaverse systems. As a result of the classification made with the active features determined using this method, there has been an increase in statistical performance criteria compared to other methods. In addition, it has been proven that time loss can be avoided in the classification of big data similar to the data used.

**Keywords**: Machine learning, metaverse systems, 3D hand posture, information gain, symmetric uncertainty ranking

## 1. INTRODUCTION

Metaverse is a software and hardware interface platform that can connect people's social lives as in the real-natural world and provide the feeling of being there at the maximum level. The expression metaverse is formed by the combination of the words meta and universe [1]. Here, while the meta means exceeding the limits; the universe is defined as a virtual environment associated with real life [1]. As authors, we would like to define the metaverse as a '*physical reality with high sensibility in the virtual environment*'.

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In the last 10 years, important developments have emerged in metaverse systems due to the rapid attack of the internet and related technologies. Especially since the whole world has passed and is going through a very dangerous deadly pandemic process, all business areas and people have had to be confined to closed environments [2]. Although this situation was not welcomed, created a disadvantage for many business areas, and caused financial losses, it was observed that especially internet and technology-based companies increased their turnover much more than in the past [2]. The leading of these is the world's big technology companies such as Microsoft and Facebook [3]. In addition to these, when we look at the investment platforms of other similar technology giants in recent years, it is seen that metaverse systems come first.

Although metaverse systems have been seen as the prominent subject of the last few years, they have actually entered the field of interest of researchers and companies with the active use of the internet. The historical stages of this process are given in Figure 1 [3] below.

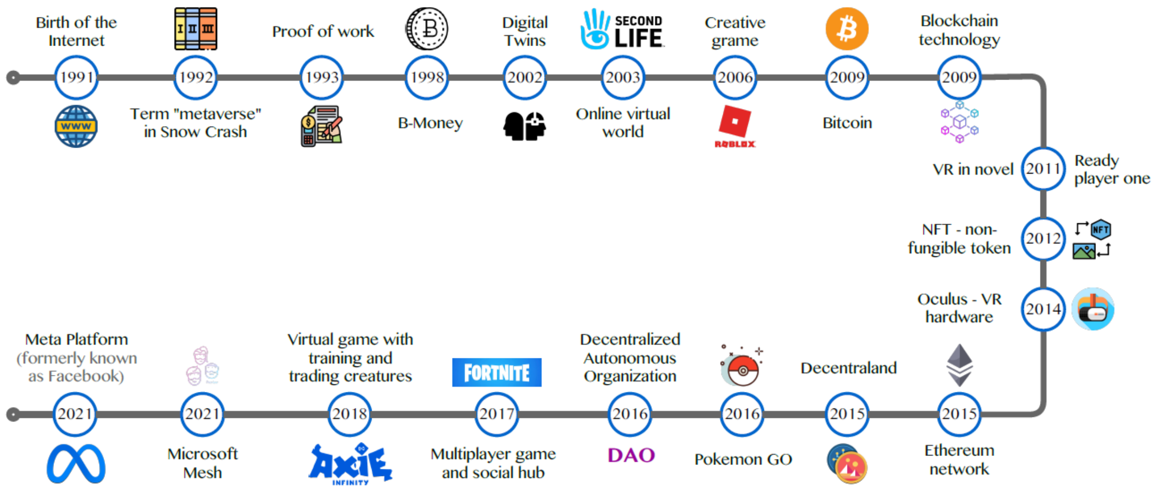

Figure 1 Historical development of Metaverse [3]

As can be seen in Figure 1, the metaverse journey, which started with the internet in 1991, continued until 2021, depending on the development of technology, and today it has been actively used in some areas (especially in the game industry). Metaverse has the potential to apply in every sector of life, from education to entertainment, from health to travel, and e-marketing. In the future, it will be possible to hold business meetings and scientific conferences through metaverse systems without the need to be physically present in the same environment [4]. However, although it is aimed to give the feeling of fully experiencing the real world virtually, the fact that the system is mostly used through hand gestures is proof that this area needs much development.

In the metaverse, the connection between the user and the extended reality (XR), which includes virtual reality (VR), augmented reality (AR), and mixed reality (MR) components, is possible with wearable devices [5]. In addition to these hardware components, it is more important that the software infrastructure is strong and a solution-maker. Currently, it is possible to integrate wearable gloves equipped with sensors, which are most actively used, into the system by using the correct solver software. As a result, it is possible with artificial intelligence algorithms to process and make sense of the data detected from the sensors in the glove and to produce an output that can move toward the virtual world.

In these systems, the first focus on gloves, among the wearable tools, is related to the fact that we mostly use our hands and fingers in daily life, high 3D posture recognition, and matching compatibility [6, 7]. In addition, it is possible for non-speaking people to express themselves through their hands and fingers. The fact that researchers turn to wearable gloves and do their analysis on them can both reach a wider audience in the real world and contribute to an important stage of the system going forward. For example, in one of these studies, a system that can recognize 15 different hand postures through machine learning algorithms has been proposed [8]. In research [9], it has been tried to detect multidimensional gesture movements by using sensor-equipped gloves to provide more realistic experiences to people in the VR environment. In another paper, it has been tried to identify 5 different hand postures for low-cost and hand prosthesis control by using an electromyogram (EMG), which are muscle signals of people [10]. In [11], researchers have proposed convolutional deep averaging Networks for hand posture detection. Nayak, et al. [12] presented the Lightboost-based Gradient boosting model for the same purpose and compared the results obtained with some machine learning algorithms. In another research study, the authors tried many machine learning algorithms, including multilayer perceptrons, where the highest performance was obtained for the detection of 3D hand postures [13]. In addition, the feature selection process was applied to the data, but it was briefly stated in the paper that no improvement effect was observed in the results [13]. In [14], a detailed literature review has been made on many topics such as the techniques, advantages and limitations of metaverse in the computer field. Within the scope of [15], research on metaverse systems of the last 20 years has been discussed and its methods and results have been examined in detail. In this respect, a research has emerged that can provide researchers with a preliminary idea about where the subject has come from and where it will go [15]. In another study that can be used in metaverse systems, the authors tried to detect 5 different finger movements by means of machine learning algorithms over the features obtained by processing the relevant signals, thanks to the wearable EMG system they put forward [16]. In a similar-purpose study that can be used in human-computer interactive applications, the researchers tried to detect 14 different hand movements through 2D images [17]. The authors of this study [18], which can enable metaverse systems to be used by speech impaired individuals, focused on detecting sign language characters through the images of hand movements.

Briefly, as can be understood from these studies mentioned in the literature, the procedures and purposes are circulating around similar phenomena. The general purpose is to detect hand posture movements with high accuracy. In order to achieve this, machine learning algorithms are also applied to reach a conclusion by evaluating the sensor data recorded from wearable gloves equipped with sensors. Although there are studies on the evaluation of meta-gloves data developed for metaverse systems with artificial intelligence in the literature, the performances of the sorting algorithms in which the features in these data are evaluated in detail have not been tested. The most prominent and generally high-performance sorting algorithms mentioned are Information Gain, Pearson's Correlation, and Symmetric Uncertainty ranking methods. In the literature, there are many studies in which these sorting techniques are applied to different data. In one of them, researchers proposed a semi-supervised system based on the Information Gain technique and they were successful [19]. A new model using in reference [20] principal component analysis and the Information Gain algorithm as a hybrid is presented. As a result of the application of this proposed model, the required features were selected along with the reduction in data size, and a high classification rate was obtained by reducing the training time [20]. Performance evaluation was made by applying three different feature sorting-selection techniques, including this ranking method [21, 22].

One of the studies in which Pearson's Correlation technique is applied is the research in [23]. Here, the effect of correlation coefficients between features on the classification accuracy of Alzheimer's disease was realized by applying three different techniques [23]. In [24], this technique was applied to the data for the classification of skin segmentation. The authors in their study [25-27] applied the method to different datasets, except for hand posture data.

Finally, when the studies in which Symmetric Uncertainty was applied are examined; in [28], a different attribute subset selection technique was introduced to analyze the symmetric uncertainty between feature-feature and feature-class. As a result, it was seen that the proposed algorithm performed better [28]. In another large-scale research study, the authors investigated the performance of 24 feature selection methods on some ready-made datasets, and it was seen that the specified method performed slightly better than the others [29]. In [30], Symmetric Uncertainty-based Maximal independent classification information and minimal redundancy feature selection techniques were proposed. In another study using this ranking algorithm, the authors developed a hybrid feature selection system [31]. The Symmetric Uncertainty method in the correlation-based system proposed here was used to detect the features to be deleted [31].

The above-mentioned feature sorting-selection techniques have been applied to some fixed-ready data sets and performance outputs that can be considered successful have been obtained. From this point of view, it is important that these methods have not been applied to the 3D sensor data [13, 32] of meta gloves suitable for metaverse systems before. In this study, the success of Information Gain, Pearson’s Correlation, and Symmetric Uncertainty ranking methods on 3D hand posture data for metaverse systems were investigated. For this purpose, various preprocessing was performed on the 3D data, and a dataset consisting of 15 features in total was created. The created dataset was ranked by three different methods mentioned and the features that the methods determined effectively were classified separately. Obtained results were interpreted with various statistical evaluation criteria. According to the experimental results obtained, it has been seen that the Symmetric Uncertainty ranking algorithm produces successful results for metaverse systems. As a result of the classification made with the active features determined using this method, there has been an increase in statistical performance criteria compared to other methods. In addition, it has been seen that the loss of time in the classification of large data similar to the data used can be prevented.

The main novelty and contributions of this research are highlighted as follows: (1) it is important that this feature sorting-selection technique, which has generally proven successful, has not been applied before on 3D hand posture data obtained from meta-gloves. (2) Thanks to this study, different application methods have already been applied to the data to be obtained from metaverse systems, which are intended to facilitate work and operation in many sectors in the future. Thus, a new path has been drawn and different perspectives have been presented to young scientists who will turn to this field. (3) It is an expected handicap that in the sectors where metaverse systems will be used, there will be intense data flow in the future and accordingly the response times of the systems will be prolonged. For this reason, it is important that the techniques that will ensure the elimination of this situation, which is highly likely to occur in the future, are applied in this paper.

The remainder of this paper is organized as follows. Section 2 introduces preparing the dataset, explanations about Information Gain, Pearson's Correlation, and Symmetric Uncertainty ranking methods. This section also gives classification and evaluation processes. Obtained numerical results, tables, graphical representations, and comments are given in section 3. The discussion and conclusion are presented in section 4.

## 2. MATERIALS AND METHODS

Gloves that are compatible with metaverse systems and equipped with sensors are known as meta gloves. Thanks to the machine learning algorithms in which the 3D hand posture data obtained from these gloves are presented as input, automatic detection of the determined movements can be made. Thanks to these applications, it will be possible for metaverse systems, which will become widespread in every sector in the future, to produce results with higher accuracy and speed.

### 2.1. Preparing the Dataset

The data used in this study were created from [13, 32] references. The data in [13, 32] consist of 3D (X, Y, and Z) values of 12 markers placed at certain points of the left-hand glove. In addition, there are three-dimensional marker values of 5 different hand signals, shown in Figure 2, belonging to 12 different subjects in the dataset.

Class information in the dataset is labeled as 1, 2, 3, 4, and 5. These label values are fist with thumb out, stop with hand flat, point-1 with pointer finger, point-2 with pointer and middle fingers, and grab, respectively [13, 32]. One of these 12 markers is placed on the back of the glove, while the others are fixed on the thumb and fingers [13, 32].

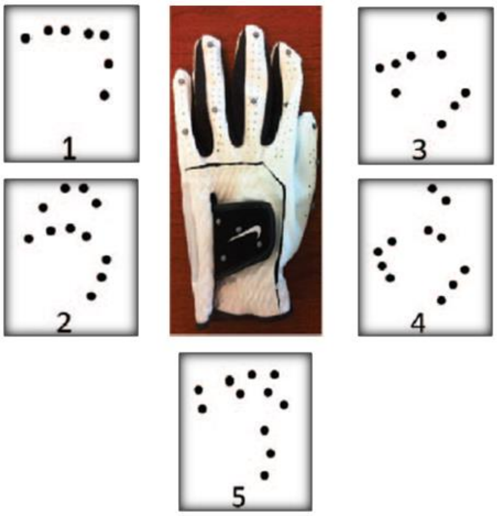


Figure 2 Glove used, and postures in the XY plane belonging to the 5-class [13, 32]

The places indicated by the '?' sign in the data set file represent the missing value [13, 32]. When the file is examined, most of the X, Y, and Z coordinates of 7 markers between 5 and 11 are given as '?'. Therefore, these markers have been ignored by us. In addition, since the same situation exists in the markers of some subjects, these parts were also removed from the data. Thus, the number of attributes, which was 12 x 3 = 36 in total, was taken as 5 x 3 = 15 (X0, Y0, Z0, X1, Y1, Z1, X2, Y2, Z2, X3, Y3, Z3, X4, Y4, Z4) and the research was carried out. Apart from this, the number of data, which is 78095 in total, has been arranged as 74975 due to missing values. As a result, the whole data set was transformed into a 74975x15 matrix, and the next steps of the study were started.

### 2.2. Information Gain Ranking

The Information Gain ranking is an evaluation algorithm based on entropy [33] and is frequently used in machine learning applications [34]. The Information Gain, which takes a value between 0 and 1, is calculated based on the number of attributes and classes [34]. Higher information gain is needed if a researcher wants better discriminating power for decision-making. Determining the relationship of features with classification is the main purpose of this method [35]. While calculating the information gain, all the data in the data set and specific data that are required to be calculated are studied. The specific data to be calculated is called "sampling data" and the calculation of this sampling data is made over the whole data set. The Information Gain calculation formula [34] is given below:

$$G(D,t) = -\sum_{i=1}^{m} P(C_i)\log P(C_i) + P(t)\sum_{i=1}^{m} P(C_i|t)\log P(C_i|t) + P(\bar{t})\sum_{i=1}^{m} P(C_i|\bar{t})\log P(C_i|\bar{t}) \quad (1)$$

In Formula 1, the *C* notation refers to the dataset array. $C_i$ is the *i* th data and $P(C_i)$ is the conditional probability of the same data. $P(C_i|t)$ and $P(C_i|\bar{t})$ represent the probabilities that the first category includes and does not include feature t, respectively [34].

### 2.3. Pearson's Correlation Coefficient Ranking

The Pearson correlation test is a statistical analysis that investigates the linearity of the relationship between related measures [36]. In addition, if there is a relationship, its direction and severity can be determined thanks to it. This analysis technique can be preferred if the data to be studied has a normal distribution. The correlation coefficient takes values between -1 and 1 [36]. The fact that this calculated value is less than zero means that as one of the two data increases, the other decreases [37]. If this coefficient is greater than zero, it means that both variables increase in the same way [37]. If this calculated coefficient is greater than 0.8, it is interpreted that there is a very high correlation. The Pearson's correlation coefficient formula is as follows:

$$r = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - \left(\sum y\right)^2\right]}} \quad (2)$$

Here x and y denote the value of the first and second variables, respectively. In addition, n represents how many x or y there are, and r represents the calculated correlation coefficient. In this study, the ranking was performed by calculating the correlation between each trait and the target class [38, 39].

### 2.4. Symmetric Uncertainty Ranking

Symmetric uncertainty is a value calculated between features and target classes and is used to determine which features are suitable for classification [40]. This method uses an information-theoretic measure to evaluate the value of constructed solutions [41]. Features with high calculated uncertainty values are considered more effective for classification than others [40]. The formula for calculating the symmetric uncertainty is as follows. In Equation 3, *H ( )*, *A*, and *B* denote entropy, any feature and class label, respectively [40].

Symmetric Uncertainty:

$$U(A,B) = 2\frac{H(A)+H(B)-H(A,B)}{H(A)+H(B)} \in [0,1] \quad (3)$$

### 2.5. Classification and Evaluation Processes

In this study, Random Forest (RF) of supervised classification algorithms was used as a classifier. This method, which is frequently used in both classification and regression processes, briefly performs the classification step over multiple decision trees it produces in order to achieve better classification performance [42]. This algorithm has been adopted and spread faster by different application areas due to its advantages such as being adaptable to the solution of many problems, being easy and flexible [42].

In the evaluation phase, the classification accuracy (ACC) parameter was primarily taken as the basis. This parameter is calculated by the ratio of the data we guessed correctly as a result of the classification to the total data set. In addition, interpretations were made by considering the Kappa coefficient and the areas under the ROC (Receiver Operating Characteristic) curve in each classification. Cohen's Kappa coefficient is a statistical method that measures the reliability of comparative agreement between two raters [43]. This coefficient, which is frequently used to prove classification accuracy in machine learning studies, takes values between -1 and +1. It can be said that success and reliability are very high in classifications where a value of 0.81 and above is calculated for the Kappa coefficient [44]. The ROC curve is a statistical method frequently used in machine learning as it defines the accuracy of the classifier itself and allows a reliable comparison between classifiers. The graphical approach of the ROC curve makes it easy to understand the relationships between the sensitivity and specificity of the measurements. The area under the ROC curve determines the accuracy of the classifier in separating instances from different labels. This area takes values between 0 and 1. When the area under the ROC curve is calculated, this value indicates a very high classification success if it is 0.9 and above [45].

## 3. RESULTS

In this study, the success of Information Gain, Pearson's Correlation, and Symmetric Uncertainty ranking methods on 3D hand posture data for metaverse systems was investigated. For this purpose, various pre-processes were performed on the 3D data, and a dataset consisting of 15 columns (features) and 74975 rows in total was created by using [13, 32] references. The created dataset was sorted by 3 different ranking methods and the features that the methods determined effectively were classified separately. Obtained results were interpreted with various statistical evaluation criteria. In this section, the details of the mentioned stages will be mentioned.

The generated data set was first sorted by the Information Gain method and then by Pearson's Correlation and Symmetric Uncertainty values, respectively. The obtained values of the features according to ranking methods are shown in Table 1.

Table 1 The obtained values of the features according to ranking methods

| **Information Gain Ranking** | | **Pearson's Correlation** | | **Symmetric Uncertainty** | |
|---|---|---|---|---|---|
| **Feature** | **Ranking Value** | **Feature** | **Ranking Value** | **Feature** | **Ranking Value** |
| **Y0** | 0.453 | Z4 | 0.1643 | Y0 | 0.0987 |
| **Y2** | 0.433 | Z3 | 0.1596 | Y2 | 0.0981 |
| **Y3** | 0.428 | Z2 | 0.1491 | Y1 | 0.0969 |
| **Y1** | 0.427 | Z1 | 0.1353 | Y3 | 0.0967 |
| **Y4** | 0.421 | Z0 | 0.1244 | Y4 | 0.0949 |
| **Z4** | 0.286 | Y2 | 0.0695 | Z4 | 0.0770 |
| **Z0** | 0.285 | Y0 | 0.0674 | Z0 | 0.0724 |
| **Z3** | 0.275 | Y3 | 0.0664 | Z3 | 0.0716 |
| **Z1** | 0.274 | X3 | 0.0663 | Z1 | 0.0715 |
| **Z2** | 0.269 | Y1 | 0.0658 | Z2 | 0.0710 |
| **X0** | 0.203 | X2 | 0.0597 | X0 | 0.0474 |
| **X2** | 0.184 | Y4 | 0.0564 | X2 | 0.0452 |
| **X3** | 0.182 | X4 | 0.0558 | X4 | 0.0447 |
| **X4** | 0.181 | X1 | 0.0545 | X3 | 0.0447 |
| **X1** | 0.180 | X0 | 0.0529 | X1 | 0.0433 |

Table 1 shows the values calculated for the properties according to the three ranking methods specified. According to the Information Gain and Symmetric Uncertainty methods, it is seen that the first 5 features whose effectiveness is specified are the same. As can be seen, only the order of the first five features has changed according to these methods. However, it is seen that the 5 features that were determined to be effective by the Pearson's Correlation ranking method are completely different. RF algorithm was used to prove which algorithm can perform statistically more accurate feature ranking on 3D posture data. According to the ranking values obtained as a result of applying the specified 3 ranking methods to the data, the first 5 features were given to the RF algorithm by one. The obtained ACC, Kappa and ROC values are shown in Table 2.

Table 2 The performance outputs obtained as a result of the classification of the first 5 features obtained according to the ranking methods by adding them one by one with RF

| **Information Gain Ranking** | | | | **Pearson's Correlation Ranking** | | | | **Symmetric Uncertainty Ranking** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Feature** | **ACC%** | **Kappa** | **ROC** | **Feature** | **ACC%** | **Kappa** | **ROC** | **Feature** | **ACC%** | **Kappa** | **ROC** |
| **Y0** | 36.1 | 0.201 | 0.695 | **Z4** | 28.8 | 0.110 | 0.617 | **Y0** | 36.1 | 0.201 | 0.695 |
| **Y0, Y2** | 67.7 | 0.596 | 0.895 | **Z4, Z3** | 47.98 | 0.349 | 0.781 | **Y0, Y2** | 67.7 | 0.596 | 0.895 |
| **Y0, Y2, Y3** | 73.69 | 0.671 | 0.931 | **Z4, Z3, Z2** | 61.88 | 0.523 | 0.797 | **Y0, Y2, Y1** | 75.83 | 0.698 | 0.940 |
| **Y0, Y2, Y3, Y1** | 77.95 | 0.724 | 0.949 | **Z4, Z3, Z2, Z1** | 67.93 | 0.599 | 0.907 | **Y0, Y2, Y1, Y3** | 77.95 | 0.724 | 0.949 |
| **Y0, Y2, Y3, Y1, Y4** | 79.73 | 0.746 | 0.956 | **Z4, Z3, Z2, Z1, Z0** | 73.25 | 0.665 | 0.932 | **Y0, Y2, Y1, Y3, Y4** | 79.73 | 0.746 | 0.956 |

As seen in Table 2, the results obtained showed that the Symmetric Uncertainty ranking algorithm was better in ranking the features of 3D posture data. Although the results are similar when the Information Gain and Symmetric Uncertainty ranking algorithms are compared, the performance difference between them is clearly seen, especially when the red line of Table 2 is examined. When the line indicated in red is examined, the Symmetric Uncertainty ranking algorithm was 2% more successful than the Information Gain algorithm. In addition, when the Kappa coefficient and the area under the ROC curve were examined, it was seen that the Symmetric Uncertainty ranking algorithm was more successful. The graphical representation of the Kappa coefficient and ROC area values of the methods is shown in Figure 3.

If Figure 3 is examined, the most unsuccessful ranking algorithm among these methods was the Pearson Correlation method. When the results of this method are examined, it is seen that its success is almost 10% lower than the others. Performance results have proven that this method is not successful in determining effective features for 3D hand posture data.

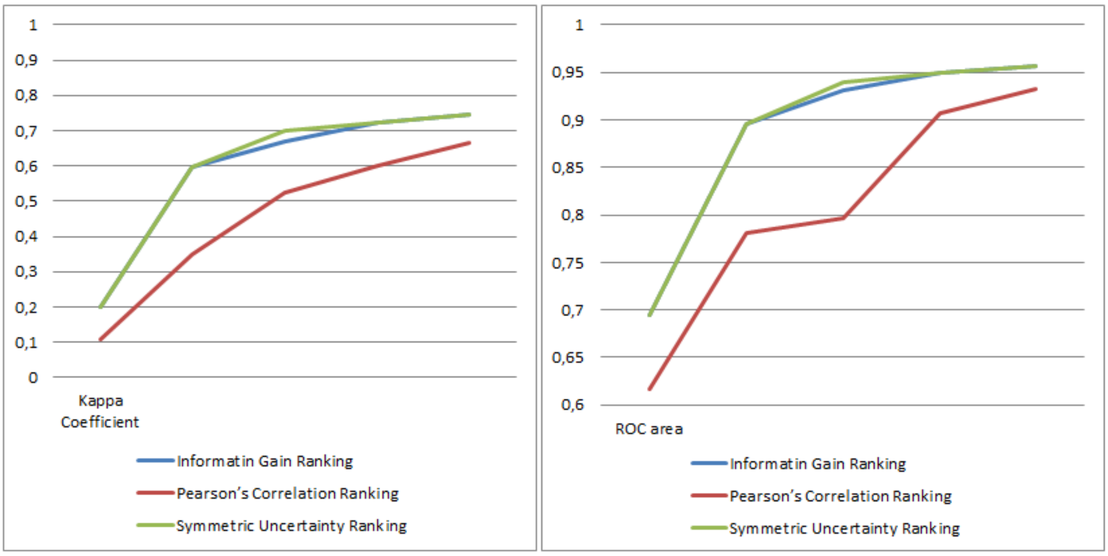


Figure 3 Graphical representation of Kappa coefficient and ROC area values of methods according to feature groups in Table 2

Table 3 The performance outputs obtained as a result of classification with RF of features determined to have different priorities according to Information Gain and Symmetric Uncertainty ranking algorithms

| Feature | ACC% | Kappa | ROC |
|---|---|---|---|
| **Y3** | 34.08 | 0.176 | 0.675 |
| **Y1** | 34.84 | 0.185 | 0.684 |
| **X3** | 25.84 | 0.073 | 0.582 |
| **X4** | 26.34 | 0.079 | 0.587 |

Finally, when Tables 1 and 2 are analyzed in detail in terms of prominent Information Gain and Symmetric Uncertainty ranking algorithms, it is seen that there is only a difference in ranking of "Y3 vs. Y1" and "X3 vs. X4" features. The results in Table 3 are obtained as proof that the Symmetric Uncertainty ranking algorithm performs a more successful ranking for the features in the specified data set. According to Table 3, when the Y1 and X4 features, which the Symmetric Uncertainty ranking algorithm determined to have higher priority, are classified separately by RF, it is seen that they achieve higher performance outputs than the Y3 and X3 attributes.

## 4. DISCUSSION AND CONCLUSION

In many sectors where metaverse systems will be applied, meta gloves are thought to be one of the most compatible hardware devices. However, it is extremely important that the 3D hand posture data obtained from the meta gloves is detected and transferred to the system with high accuracy as a result of the necessary processes. Because if the movement reflected on the glove is perceived as wrong at first, it will inevitably cause problems chaining in the whole system. In this study, the success of Information Gain, Pearson's Correlation, and Symmetric Uncertainty ranking methods on 3D hand posture data for metaverse systems was investigated in order to avoid possible problem chains in these systems, which are thought to have very common areas of use in the future. For this purpose, various pre-processes were performed on the 3D data and the created dataset was ranked by three different methods. Then, the features that the methods determined effectively were classified by the RF algorithm separately. Obtained results were interpreted and it has been proven that the Symmetric Uncertainty ranking algorithm is more successful than the others. On the other hand, it was seen that Pearson's Correlation ranking method was the most unsuccessful among the methods specified in ordering the effectiveness of the features of these data.

As with other similar studies in this area, this study also has some limitations. One of them is data diversity. Today, the active use of machine learning algorithms in daily life, increasing the current success rates and reliability is possible by presenting many data from different sources to the systems. This is a common and general limitation of all sectors and research areas where artificial intelligence algorithms are used, not only for posture data. Another limiting factor for similar studies is meta gloves. These are important for metaverse systems because they collect and regularly transfer the 3D hand posture data of the relevant movements to the system and start and execute the processes over these data. For this reason, the wrong position of the sensors placed in the glove and the incomplete/incorrect quality of data detection and transmission are seen as limiting factors.

Apart from the ones mentioned above, it is certain that the noise level of the data transferred in current and future research will also affect the accuracy of the evaluations. Therefore, in the future, different studies can be carried out on noise detection, noise removal, and application of various filtering techniques on different data and comparative evaluation of the results. Another research that can contribute to this field may be on eliminating the missing data, which is not very intensive, by various methods and investigating its effects.

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The authors contributed equally to the study.

***The Declaration of Conflict of Interest/ Common Interest***
No conflict of interest or common interest has been declared by the authors.

***The Declaration of Ethics Committee Approval***
This study does not require ethics committee permission or any special permission.

***The Declaration of Research and Publication Ethics***
The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science

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