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An innovative framework for the recognition of human activity in smart healthcare

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***Abstract*---**Health services are one of the most difficult aspects of the massive influx of people into urban centers. With global digitization, especially in healthcare, the ability to collect, receive and present data has become a top priority**.** Currently, many applications in the healthcare business use Machine Learning to give individualized therapies, which will be more dynamic and efficient once personal health and predictive analytics are combined. Furthermore, machine learning-based tools aid in the treatment of patients starting at the ground level, with clinical practice diagnosis and suggestions. Massive amounts of data may be collected from smart devices in our digital age. Human activity recognition is a classification problem in which data is used to identify events performed by humans. This data is categorized and analyzed to discover patterns in the data that may be used to create future predictions. In theory, activity detection can provide significant societal benefits. Activity recognition and pattern discovery are two aspects of human activity comprehension. The first is concerned with detecting human activities accurately using a specified activity model.

***Keywords*---**health sciences, machine learning, recognition system, smart applications.

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Introduction

Artificial Intelligence includes machine learning as one of its components. To aid decision-making, it prepares and discovers patterns in massive data volumes [1]. Pattern recognition is the process of identifying patterns using machine learning techniques. It categorizes data using statistical data or knowledge derived from patterns and their representation. Pattern recognition systems are trained using labeled training data in this method. Big data, which contains large amounts of unstructured data, is a resource that can be used less that can help businesses make better decisions and improve jobs, especially in the healthcare industry [2].

As data becomes more and more complex, many medical research institutes and businesses are turning to predictable analytics to tap into that source and gain a competitive advantage. Guessing statistics is a mathematical formula that uses statistics (both historical and current) to estimate, or 'predict,' future results. Includes several mathematical strategies (including machine learning, predictive modeling, and data mining). These consequences, in the instance of this article, might be behavior that a user is expected to show as part of their everyday routine [3]. By evaluating the past, predictive analytics can help us understand possible future events. Healthcare organizations are seeking to make big digital changes. Data mining tools may make this big digitalization of the healthcare environment go more smoothly. This transition with numerous smart devices generates a huge amount of data, which may be analyzed via data mining to gain a deeper understanding of people's daily life [4-8]. We may be able to predict human health conditions using specific smart devices based on variations in appliance usage at home. Any changes in appliance usage are noted and recorded over time, showing that people are having trouble caring for themselves.

Using large data home intelligence, this study proposes a function (HAPP) approach. It can study and pinpoint human patterns from appliance usage of individual households for applications in the medical community. The proposed method uses conventional pattern mines, analysis of groupings, and forecasts for energy monitoring and quantification variability caused by community behavior. The HAPP software examines the energy consumption tendencies of electrical items associated with human activities. Smart meter data is mined repeatedly in a 24-hour quantum/data session, and the results remain unchanged throughout the mining periods.

Related Work

[9]In this paper, job identification is seen as important in closing the gap between low-level sensors and high-performance applications. Multiple sensors have been used to achieve optimal diagnostic quality and adapt to different operating system settings, with Smartphone embedded inertial sensors commonly used due to their simplicity, low cost, and interference. In this study, we investigate the smartphone's built-in triaxial accelerometer and gyroscope to detect the actions of the human body in situations where they are used and or independently.

[10-12]A key feature of the selection process is then proposed to select a smaller set of discriminatory features, create an online functionality with better

performance capabilities, and reduce smartphone power consumption. The proposed feature selector works better than the other three comparison methods in terms of four performance measures, depending on the test results in the publicly available data set. Your combination of both accelerometer data and gyroscope results in better recognition performance than using single-source data, and the proposed feature selector works better than the other three comparison methods in terms of performance measurements. In addition, significant improvements in time performance can be made with the active feature selector, which shows how to save energy and your performance in real-world job recognition.

[13 - 16]This study describes a method for using wearable sensors to recognize human activities. The continuous autoencoder (CAE) is a revolutionary stochastic neural network model that increases continuous data modeling ability. To extract indirect data features, CAE integrates random Gaussian units into a simulated sigmoid activation function. We are introducing a new fast stochastic gradient descent (FSGD) method for updating CAE gradients to reduce training time. Swiss-roll database reconstruction demonstrates that CAE can inject more continuous data than conventional autoencoder and that the FSGD method can reduce training time. The Temporary and Common Domain (TFFE) feature method is used to exclude features in human performance recognition tests.

Proposed Methodology

The proposed study's purpose is to develop a successful Human Activity Pattern Prediction system (HAPP). The proposed model employs a variety of powerful machine learning and data mining techniques to successfully extract information from the renters' everyday appliance usage. Smart meters are smart gadgets that we utilize to acquire the above-mentioned data. Smart meters are incredible devices that can capture a wealth of information about human activity. The data is gathered and can be progressively mined in real-time to extract important information by identifying emerging patterns in the data. This can be used to make predictions that have real-world implications.

The Frequency Patterngrowth algorithm is a mining technique, the most frequent pattern from anomalous human behavior based on their daily activities. We also apply k-Means which is a clustering technique that takes input data points from collected smart meter data and groups them into k clusters. This allows it to cluster the use of different appliances, whether they are utilized one at a time or simultaneously. To make predictions from inferred data after applying both FP Growth and K-means we use BNN which is a type of neural network that blends Bayesian inference with neural networks. When dealing with unknown targets, the BNN model provides a complete view of the forecast, allowing you to automatically quantify the uncertainty associated with your prediction. Thus, the developed HAPP model can foresee the use of various appliances/gadgets and generate successful predictions.

As discussed above we can infer the main steps in the proposed methodology required to build the model.

1. HAPP framework according to smart home variations in gadgets used. The HAPP model incorporates both appliance-appliance and appliance-time associations for improved accuracy.
2. For pattern recognition, this model employs FP growth.
3. To find the relationship of an object with time, this model uses the k-means integration algorithm. Growing mines are used to achieve this.
4. For work predictions based on the use of individual machines and more, use the Bayesian network.

The proposed HAPP system has four main stages that work together to achieve the desired results.

- Data preprocessing: Raw data is converted into an easy-to-understand format. Before applying machine learning or data mining algorithms, you need to check the quality of your data.
- Feature Extraction: The information in the original data collection is preserved so that the data is transformed into process-able numeric features. This gives greater outcomes than if machine learning was applied to raw data directly.
- Model Development: After that, the dataset is consolidated using machine learning techniques. To do this, we depend on various classification and ensemble techniques.
- Model Evaluation: Evaluation of the model is done in this stage.

Table 1: Basics Statistics

	Cooker	Running machine	Toaster	Washing machine	Rice cooker	Kettle	Microwave	Dishwasher
Count	878300	878300	878300	878300	878300	878300	878300	878300
Mean	0.17	2.89	0.589	11.28	2.93	22.2354	6.7	39.52
Std	4.92	15.10	16.71	120.35	27.03	249	91.05	271.65
Min	0	0	0	0	0	0	0	0
25%	0	1	1	0	3	1	0	1
50%	0	1	1	0	3	1	0	1
75%	0	1	1	1	4	1	0	1
99.9%	10	297	298	1	2194	407	1333	2040
99.99%	10	373	373	972	2306	413	1357	2062
max	3521	719	2365	2975	808	3997	2668	3960

Algorithms Used

The FP-Growth Algorithm is a cost-effective approach for mining the entire subset of the original trends by sequence remnant expansion, which uses an extensive prefix-tree configuration for warehousing condensed and pivotal details concerning recurrent trends. The above-specified algorithm is a different method of locating common or frequent itemsets. It differs from the Apriori algorithm in that it encrypts the data set using the FPtree and then extracts the set of frequent itemsets from this tree. There really are 2 constituents to this portion: the first part deals with the FP representation tree and the second part deals with the frequency with which item sets are generated using this tree and its algorithm.

A concise database prototype that expresses a statistical model as a tree is an FP tree. So each transaction is collected and then plotted to a tree path. Until enough operations have been read, this loop is continued. Because their trajectories intersect with other transactions, different transactions contain similar subgroups that preserve the tree compact. There are three major processes to constructing an FP tree.

The steps for construction of an FP tree are explained below

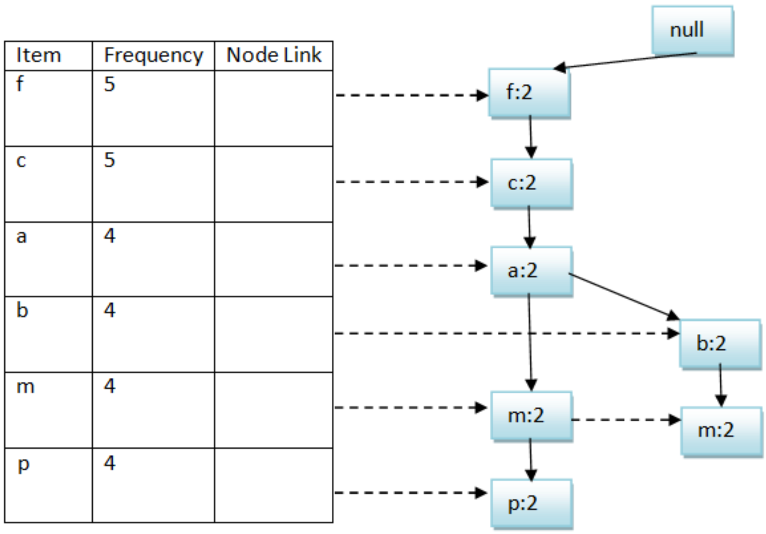

Figure 1: FP growth

1. Analyze the crawl to find the number of times each item was supported, then remove the infrequent items and sort the frequent components in the sliding down rule.
2. To create the FPtree, analyze the data set one by one. Each transaction must have the following information:
   - If the transaction is unique, create a new path and set each node's counter to 1.
   - If it shares a common prefix element set, increase the number of nodes of the common element set and, if necessary, add new nodes.
3. If it has a common prefix element set, increase the number of nodes of the common element set and add new nodes as needed.

Results and Discussions

Kmeans is a centroid or distance-based technique where the distance between points is calculated to allocate a point to a cluster. So k-means is an algorithm that allows you to cluster your data and as we will see it is a very handy tool for discovering the categories of clusters in your data set that you will have not thought of arriving. What Kmeans does for us is remove complexity from this decision-making process and make it easier for you to determine what performed better than the other classifiers. Overall, we used the best machine learning techniques to predict and achieve high-performance accuracy. The following figures show the result of these methods.

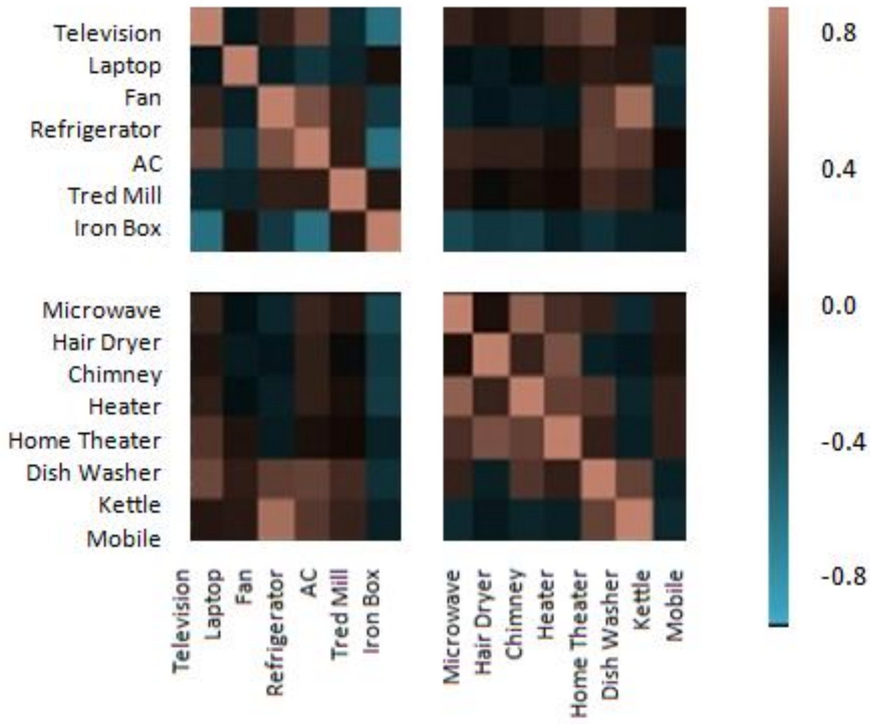

Figure 7: Correlation Matrix

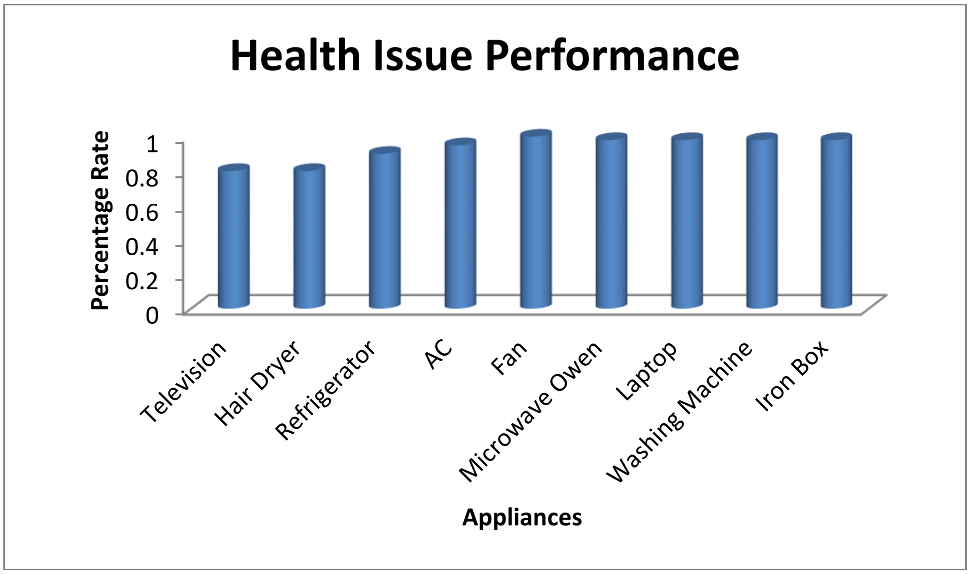

Figure 8: Health Issue Rating for different Appliances

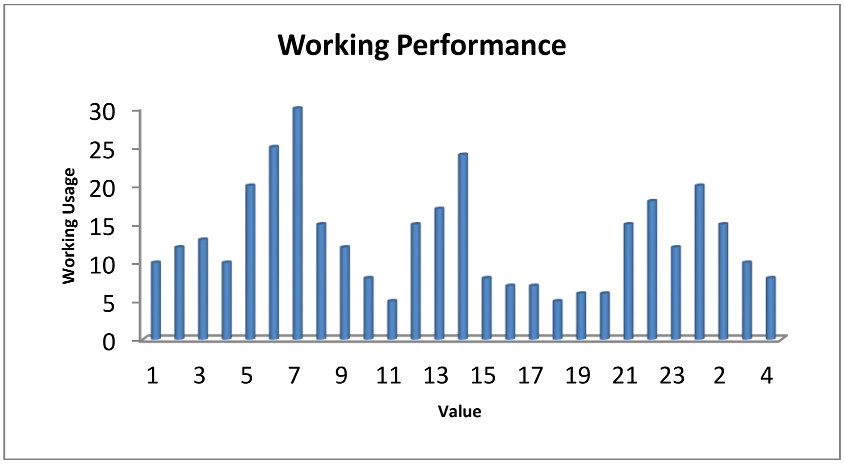

Figure 9: Working Performance of Applications

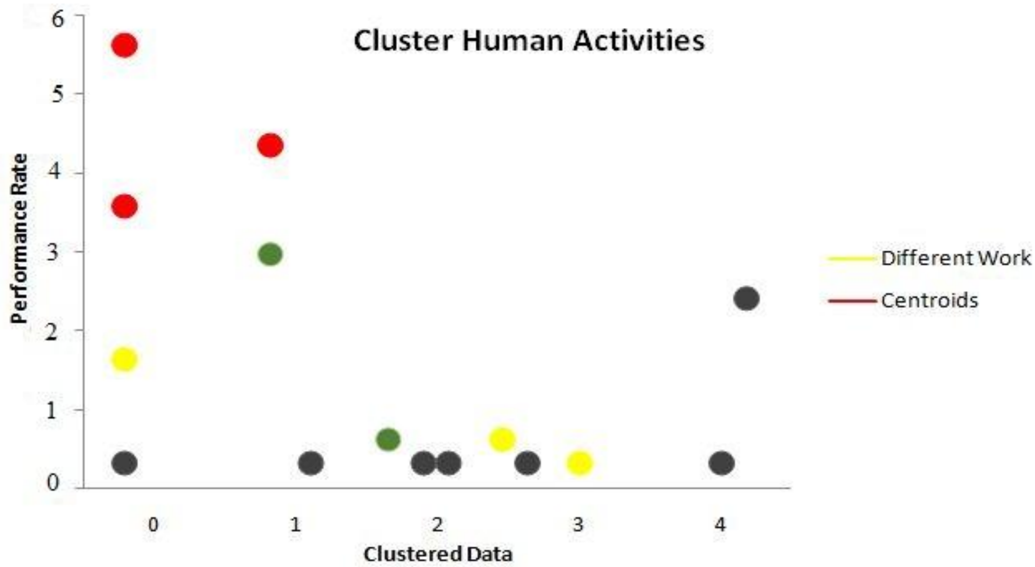

Figure 10: Performance Rate across clustered human activities using k-means

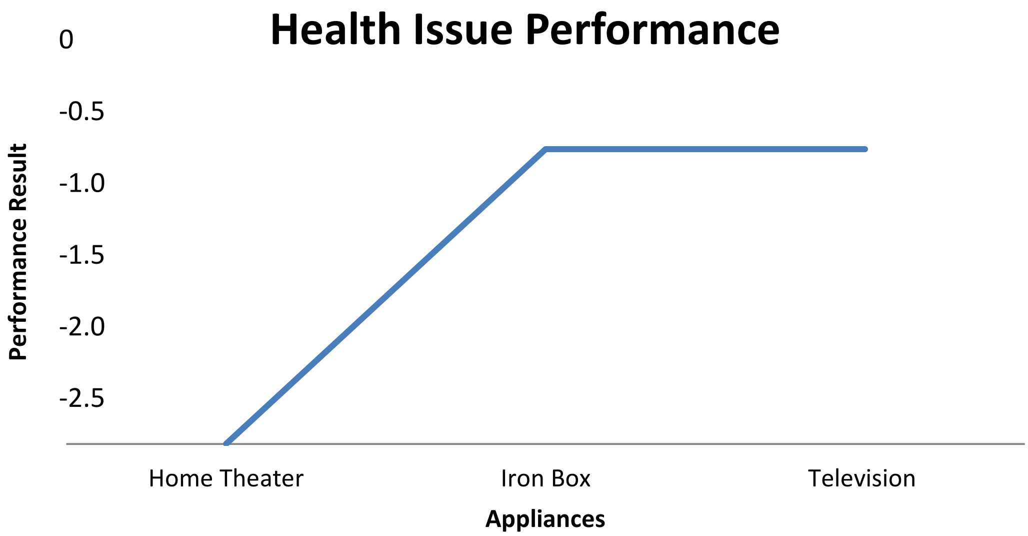

Figure 11: Health Issue Performance

```
Prediction score is [-3.3275] for [Home Theater]
-3.327534975662643
Health Issues Happened
Prediction score is [+0.1609] for [Television]
0.16085210010684037
Health Issues Happened
Prediction score is [+0.1815] for [Air Conditioner]
0.18146947357291396
Health Issues Happened
Prediction score is [+0.8085] for [Chimney]
0.808451168428693
There is no health issue
Prediction score is [+0.8145] for [Hair Dryer]
0.8144685232976889
There is no health issue
Prediction score is [+0.8347] for [Refrigerator]
0.8346536688428511
There is no health issue
Prediction score is [+0.8975] for [Microwave]
0.897468538617201
There is no health issue
Prediction score is [+0.9754] for [Kettle]
0.975434304835172
There is no health issue
Prediction score is [+0.9998] for [Fan]
0.9998439427088534
There is no health issue
Prediction score is [+1.0000] for [Dish Washer]
1.0
There is no health issue
Prediction score is [+1.0000] for [Heater]
1.0
There is no health issue
Prediction score is [+1.0000] for [Iron Box]
1.0
There is no health issue
Prediction score is [+1.0000] for [Laptop]
1.0
There is no health issue
Prediction score is [+1.0000] for [Tred Mill]
1.0
There is no health issue
Prediction score is [+1.0000] for [Washing Machine]
1.0
There is no health issue
['Home Theater', 'Television', 'Air Conditioner']
```

Figure 12: Prediction Result DecisionTree Regressor

Conclusion and Future Work

The principal intention of this endeavor is to design and implement a method to predict human activity patterns and to create an efficient human activity pattern prediction system. It is actually done using machine learning methods and analyzing the performance of these methods. Furthermore, we have additionally used neural networks like BNN to cement this proposal of HAPP which has numerous societal benefits. The outcomes of the experiment can aid health care by assisting in making early predictions and making early decisions to save people's lives.

This concept has a lot of potential for growth. For starters, activity identifiers can be refined through transfer learning. Copiously bigger datasets can be put to leverage to reduce model inaccuracy. Introduction to Learning Distributed Big Data mining from multiple residences would be an interesting project to work on. Furthermore, public internet and portable implementations can be constructed to call these python modules through an Access token to focus on providing the potential to distinguish the user's mobile activity, as well as to assist the aged and vision-impaired folk in comprehension and engaging with their environment, and many other real-time activity recognition applications.

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