HUMAN ACTIVITY RECOGNITION USING WEARABLES

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ABSTRACT

In spite of developing a smart environment around us, Human Activity Recognition (HAR) helps as a major hand. We can recognize the human activities by embedding the sensors in the wearable gadgets which are carried by them all the day. As this system will go through all the noise and distortions, some operation modules are followed by the system such as data acquisition, preprocessing. Various state-of-the-art techniques had recently presented feature extraction and selection algorithms that can be categorized using conventional machine learning classifiers. However, the majority of the solutions make use of rustic feature extraction techniques that cannot distinguish between complicated activities. Many HAR systems use deep learning techniques to quickly gather features and classify data.

KEY WORDS

Activity recognition, Internet of Things, wearable sensors, context-aware, deep learning.

INTRODUCTION

Wearable sensors have become increasingly important in recent years, both in terms of research and application domains. Their use in several applications is the cause of this attention.

It has been made possible by a steady decline in their price and size. Wearable sensors for sports and physical activity, surveillance, human-computer interaction, therapy, and geriatric patient monitoring for Ambient Assisted Living (AAL) are a few examples. The latter is particularly significant because, in both social and economic contexts, the current trend toward an ageing population is universally acknowledged as a major issue.

AAL technology could aid in the development of active ageing scenarios, preserving the quality of life of the older population while lowering the demand for social and healthcare services. The large number of research efforts and programmes (such as the "active and assisted Living joint programme") demonstrate the topic's significance on a global scale.

One of these is Human Activity Recognition (HAR), which is significant because it acknowledges the link between an active lifestyle and health. As a result, users' lifestyles can be evaluated by keeping track of how much they do each day and eventually developing a behavioural model that might be helpful for the early detection of anomalies that might be important to wellbeing.

Additionally, it is crucial to precisely analyze the user's activities (such as walking, ascending/descending stairs, etc.) in order to create a precise behavioural profile.

In order to detect single users' everyday actions in an AAL environment, the HAR system presented in this study was created to make use of the potential of wearable and smart gadgets. It is built using wearable sensors with Area network and Deep Learning algorithms. In summary, the suggested features make use of Wi-Fi connectedness and a classification techniques that is intended to be utilized in the web again for task that involves its most calculation (the training and testing) and on an integrated unit or even a cheap local smartphone again for task of detecting everyday actions. The only time a link to the cloud provider is necessary, in this viewpoint, occurs when a new topic is introduced to the tracking system. The one and only time a link to the cloud provider is necessary, in the this viewpoint, if a new topic is introduced to the tracking program. This allows for a brief period of retraining and the creation of a dataset that is fully appropriate for the use case.

The goal of this effort is not to identify elderly people's activities in real time, but rather to monitor their daily activities over time on a personalised basis in order to identify anomalous behaviours, which are frequently indicative of sick conditions or emergency circumstances.

LITERATURE SURVEY:

- From [1], the following inference is collected. The automatic extraction of features for effective human activity classification is growing significantly, and it has a broad application across many disciplines. This is due to the continual increase in processing resources like GPU devices as well as the ease with which sensory inputs from smartphones and wearable technology may be collected. Finally, open issues that must be addressed in order to forward future research are also covered.

- The [2] paper presents the classification performance of three different machine learning algorithms based on SVM, HMM and ANN. In order to improve the 1-vs-All classification performance, other features, such as age, weight, statistics of acceleration, physiological measurements of the subject during a specific activity, etc., can also be taken into consideration.

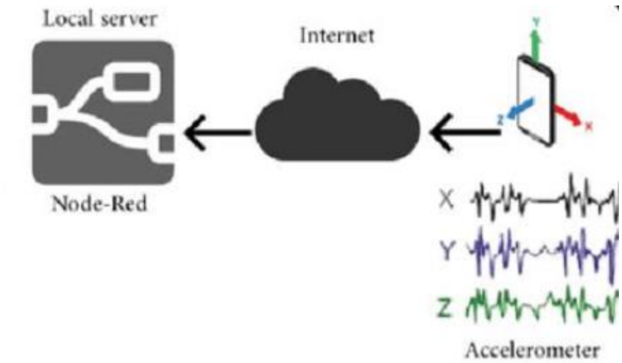
- Human Activity Recognition has become a common application in several emerging computer 399 domains thanks to the sensor industry's growing expansion and technological improvement However, in the majority of cases, researchers are unable to acquire a suitable benchmark dataset to finish the algorithm training. As a result, it recommended carrying out the HAR job utilizing a thorough study of the previous activity recognition dataset using the human point cloud benchmark dataset from the new NodeNs sensor. The suggested dataset has a greater detection performance accuracy and is more significant for actual issues as compared to the present benchmark dataset. Future research projects may take into account hardware resource consumption, including memory, CPU, sensor count, and battery life. Further research should be done on the most common tradeoffs between recognition accuracy, precision, and resource utilization.

- On a wearable IoT device with stretch and accelerometer sensors, we provided a HAR framework. Our approach starts with a cutting-edge method for unevenly segmenting sensor data in response to human motion. The segmented data is then used to create FFT and DWT features. Nine users participated in experiments on the TI-CC2650 MCU, which demonstrated 97.7% accuracy in identifying six activities and their transitions while using less than 12.5 mW of power.

- This work suggests a 1D CNN and deep learning-based activity classification method. The hardware was a wearable inertial sensor, and the software made use of an activity recognition algorithm. The three-axis acceleration and three-axis angular velocity data were extracted by the activity recognition algorithm from motion signals picked up by the sensor. The total accuracy of the open dataset was 98.93% in the training data and 95.99% in the testing data, whereas the overall accuracy of the data this study recorded was 97.19% in the training data and 93.77% in the testing data. The experimental outcomes successfully confirmed that the proposed CNN could be regarded as an efficient method based on inertial sensors in recognizing common human activities and can be used in the future to assess the volume of rehabilitation exercise of people with reduced mobility, such as dialysis patients. This confirms the viability of the algorithm we proposed.

WORKING MODEL:

Figure 1 illustrates the system design. The data that the wearable sensor collects is transferred to the cloud for training, but can be further explored in daily use. board or transferred to another machine for additional processing. Data that has been produced offsite for model reasons was utilized to make those sets which were utilized to develop the human cerebrum depicted in this review.



A. *Hardware Platform*

The information assortment framework includes a Wi-Fi wearables that gathers information and sends it IoT-compliantly to a cloud service. The sensor based prototype is built on the MPU9250 combined inertial measure (Fig. 2). (IMU, equipped with a magnetic, gyroscope, and 3D accelerometer). The create optimal is linked to a control panel (Launch Pad XL board) with a Texas Instruments scheme (SoC) that includes the ARM CortexM4 Pic Microcontroller Unit (MCU). It has a systems administration microchip that is viable with IEEE 802.11b/g/n ip radio and a 32-cycle design running at 80 MHz.
There might be a lower, more agreeable board makeover.
Launch Pad Board:

Micro Controller Unit:

The complete scales of the sensors are programmable, and they have been programmed to detect accelerations up to 8g, have a magnetometer sensitivity of 4800T, and a gyroscope full scale range of 250°/sec. Each sensor's sampling rate has indeed been set to 50Hz. The output of the actual device is a sort numbers list (3D output from sensors such an acceleration, gyroscope, and magnetic), which corresponds to 16 bits and 18 bytes with only an axis sign. For training purposes, two bytes that carry the user's unique number and a signaling for the real action that was taken have been included. To achieve the latter, the select a sample size was required to adhere to a predetermined protocol (i.e., the order of the tasks) and press a button on a worn sensor and when an action changed. After clicking the button, the subject performed each action, which started a count in the device's firmware to begin counting. Each action was then given a matching counter number. No sound filtering was applied to the data.

An essential step in using a device is setting up the network, which joins the wearable sensor to such Internet via Wi-Fi home router When a user hits the phone's button, feedback is given by an unique LED lighting pattern. The extremely simple establishment process utilizes the Wi-Fi Got Arrangement (WPS) standard. The client can finish the establishment interaction themselves on the grounds that no specialized information is required. Utilizing the MQTT convention with such a Nature of Administration (QoS) level of 2, which guarantees that the message is only ever earned by the intermediary once and thus provides the essential durability for the transmitted data, data are provided towards the online Watson Network infrastructure provided by IBM Bluemix cloud services. The letter's content is a text file in Json that contains information about the devices' status. Nevertheless, the device's firmware allows for connection to certain other platform too though (such as Thing speak, Microsoft Azure, Amazon AWS, etc.). Each wearable device has a distinct ID so that the service provider can manage its affiliation with the cloud environment, creating a true "plug-and-play" experience.

In general, the collected data aren't particularly important by itself, but analysis is needed to provide knowledge that is (for example, data seeing genuine client action like strolling, sitting, and so on.). We could ponder sending every sensor information to the cloud for additional handling and examination. This could imply that the gadget's radio part, which utilizes one of most energy, is dependably on, lessening battery duration. The use of sensor energy must be taken into account in order to demonstrate the correctness of the entire method. A low limit battery (Li-Particle 4.2V, 500mAh) has been decided to consider true use situations (battery limit is confined by ergonomic impediments: size and weight).

For the investigation of human development highlights, it was shown that an examining recurrence of 50 Hz, a battery limit of 500 mAH, and an entire 9 degree days information datum might accomplish a long period of less then 8 hours.

As a result, using such an approach in a practical environment is unfeasible. Battery life can be extended by adding compression techniques or other on-board platform helps. For instance, by combining data into longer bursts and using internal memory for buffering, we can significantly reduce the transmission overhead. The final result is entirely on alignment with the goals of such a effort.

B. *Selection of the Neural Network Model*

The approaches utilized in the fields of extracting features and signal processing have undergone a major change as a result of the advancement of deep learning. In fact, during the feature based procedure in the past, property features were created by manually examining the signals in each of their component parts. Then, statistical and traditional machine learning algorithms were trained using the washed data. The disadvantage of these methods is that they would need signal and domain expertise for each data set or sensor to investigate the essential information and gather the qualities for a model.

One more key limitation of an AI technique in exercises distinguishing proof is the test of summing up the model against the scope of movements created by particular people.

To avoid restricting the computational resources made available by a cloud provider yet taking into consideration the application environment, we zeroed in on making instructing techniques that could join productivity with framework prerequisites. In explicitly, we considered: the requirement for automated feature extraction. In order to meet our objectives for edge detection and achieve the highest literacy development, we focused on architectures. Another factor driving this need is the latest recent HAR research.

A simple learning model is necessary. We developed and trained a thin neural network, which can easily be translated to reduced or embedded systems and can draw conclusions with the least amount of resources.

So, instead of manually engineering features, we examined a deep learning-based strategy in this study to categorize signal data, relying only on a brief preprocessing stage that will be discussed later.

Recurrent neural networks (RNN) and convolutional neural networks (CNN) are the cutting-edge deep learning architectures. RNNs are frequently used in the HAR area, especially the variant incorporating Long-Short-Term Memory gates (LSTM).

The recommended device has been used to collect a dataset, and exploration tests on an LSTM and just a CNN already published in literature have been run to see which design could perform the best in our circumstance.

The information assortment stage affected 15 individuals, 12 men and 3 ladies, ages 25 to 50, who took similar concentrate multiple times on various days. The respondent was told to do the most continuous day to day errands (Table I) in a foreordained request while wearing the sensor in a belt during the test.

TABLE 1: ACTIVITY TABLE

ACTIVITY ID	ACTIVITY
1	Lie down
2	Climbing stairs down
3	Climbing stairs up
4	Stand
5	Running
6	Walking
7	Stay seated
8	Standing-up
9	Sitting-down

TABLE 2:
ACQUISITION DATA PROTOCOL

COUNTER	ACTIVITY ID	ACTIVITY
1	4	Stand
2	6	Walking
3	3	Climbing stairs up
4	2	Climbing stairs down
5	6	Walking
6	5	Running
7	9	Sitting-down
8	7	Stay seated
9	8	Standing-up
10	4	Stand
11	6	Walking
12	3	Climbing stairs up
13	2	Climbing stairs down
14	5	Running
15	9	Sitting-down
16	7	Stay seated
17	8	Standing-up
18	1	Lie down

The data's organisational structure consists of UserID, clock, 3D linear velocity (x, y, z), 3D rotational rate, and 3-dimensional magnet data.

The accelerometer, gyroscope, and magnetometer sensor signals were gathered and pre-processed using sampling in fixed-width sliding windows with 50% overlap and 2.56s of time (128 readings/window).

Since there isn't much time left, real-time data processing would be possible. The inference step might thus be integrated into the sensor, opening the way for creative improvements. The result was the creation of a database of 15616 occurrences, which was subsequently divided as indicated in Table III.

TABLE III:
COMPOSITION OF DATA

% OF INSTANCES	ACTIVITY
2.7	Lie down
14.8	Climbing stairs down
16.5	Climbing stairs up
12.0	Stand
9.4	Running
26.1	Walking
11.9	Stay seated
2.6	Standing-up
3.6	Sitting-down

This dataset served as both the test dataset and the test set. Three potential divisions of the information in the test and training sets have been studied in order to decide which architecture is better appropriate for our systems and to examine how well LSTM and CNN systems perform in various circumstances.

The primary situation, where people thought about an inconsistent split (where generally 60% of the circumstances were placed into the preparation set and the getting by into the test set), is actually very ridiculous in spite of the way that this division is usually utilized in light of the fact that an inadequately adjusted scattering of the cases between both the train and test could happen.

In the subsequent model, we considered five clients again for test set (who were not the same as the clients in the preparation set) and nine cycles of ten people for the preparation dataset. For this situation, the organization is prepared utilizing a bunch of people who were not considered during in the organizations working stage. This requires the network to be trained once using a collection of or before data when it is actually deployed in a realistic situation; the system does not have to be reeducated if a new man is being observed.

In the third case, the training set's six repetitions and the test set's nine repetitions were divided among the 15 users (3 repetitions). The network in this instance has been trained on all users who were observed during the running period. The finest outcomes with this situation are anticipated. The network must be trained on the same people that will be observed, which is a labor-intensive process that uses a lot of processing power. Actually, using the sensor's Wi-Fi transceiver and cloud connection would be a better idea than the original plan. Every time a fresh user is taken into account, a short preparation cycle can be arranged: the client is told to follow a particular movement convention, following which the sensor's information are shipped off the cloud where, utilizing cloud examination, an organization preparing interaction can be directed. The modified factors of the organization customized to identify the exercises with the best exhibition are then put away on the wearable to complete HAR ready if a lightweight enough counterfeit is accessible.

The HAR analyzed data can then, if needed, be communicated with other users by uploading them to a cloud provider (physicians, caregivers, etc.). The same batch size and number of training epochs (1000) were used for all experiments (600).

The outcomes demonstrated that CNN can achieve slightly greater accuracy levels (approximately 2%) than LSTM designs.

Table IV provides the accuracy results from the initial experiments using CNN.

TABLE IV:
PRELIMINARY RESULTS

ARCHITECTURE	**SCENARIO-1**	**SCENARION-2**	**SCENARIO-3**
CNN	90%	82%	91%

These findings support the third scenario's superior performance.

C. *Optimization of the CNN Model*

Considering the fundamental outcomes, we chose to assemble the framework utilizing the CNN design, enhancing the model utilizing the best techniques proposed in the writing.

The Boundary Rot procedure (LRD), a framework search over the really high energy that can influence the presentation of a model, and a number of trials with alternative network architectures (changing the hidden layer count and their typology) were utilised to get at the optimum. The most accurate network architecture has been chosen. Before introducing the output layer, each structure had a Dropout layer with a value of 0.5. The output layer's activation function has been a Softmax (eq. 1).

$$P_i = e^{a_i} / \sum e^{a_k}$$

Where computer based intelligence is a part of the info hubs of N real figures, and pi is the still up in the air by normalizing with the all out of all exponentials. The Softmax capability is to change over an organization's non-standardized yield into a back circulation. Also, a grid-search has been performed for each structure across the following hyper-parameters:

With a 0.005-step increment, the searching range is (0.0001 to 0.04); the parameter is

64,128,256,600 assessed values in the batch

With a search window of 500 to 2500, there are 500 training epochs.

Table V presents the findings.

TABLE V: COMPARISION OF DIFFERENT CNN STRUCTURES

N^0 CONVOLUTIONAL LAYERS	N^0 FULLY CONNECTED LAYERS	ACCURACY
2	1	92.80%
3	2	93.60%
3	1	93.80%
4	1	93.80%
4	1	94.20%

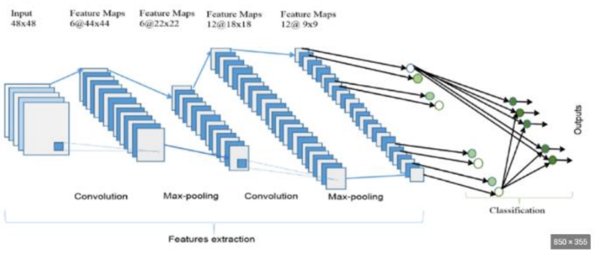
The structure with the highest accuracy contains 4 convolutional layers, 1 fully connected layer, a learning rate of 0.0001, 256 batches, and training data.

2500 epochs are used here. For the suggested system, this architecture, shown in Fig, has been chosen.

The objective of each convolutional is to include extraction from the organization's feedback. It comprises of two parts: a convolution activity (eq. 2) applied to I (preparing model I-j input grid) and K, and a greatest pooling activity (channel m-n framework).

$$g(i, j) = (K * I)(i, j) = \sum\sum I(i - m, j - n)\, K(m, n)$$

The Upsides of k are thusly found with the utilization of the Back Proliferation. The produced lattice g is then down tested by the pooling layer administrator (i,j). This last step assists in reducing the computing cost by lowering the number of characteristics that must be evaluated. Last but not least, the fully linked layer is built using traditional neural network architectures.



The models has been optimised after the framework has been determined using LRD and a fresh grid search. The proportional gain variable must have a starting value for the LRD to start optimising through the training epochs. The model is able to attain an efficiency of 94.75% utilising the ideal place for the high energy provided in Table VI with the aid of the last grid search (Fig).

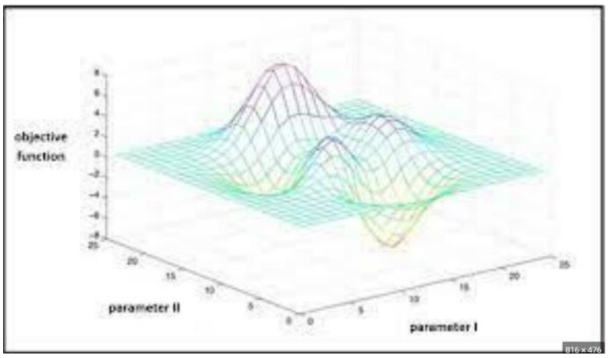


TABLE VI

THE IDEAL ARRANGEMENT OF THE HYPER BOUNDARIES:

HYPERPARAMETER	BEST VALUE
Learning Rate	0.006
Learning Rate Decay	0.95
Epochs	999
Batch size	602

The organization structure that has been ideally tuned can be refreshed, imported, and utilized in the structure of our framework to determine new outcomes.

EXPLORATORY OUTCOMES:

The viability of the past report further developed CCN model has been assessed by a couple of tests. Two datasets were utilized: a regular information from the UCI AI Store and a fresh out of the plastic new dataset. Data from the sensing layer will be obtained using these datasets. Performance metrics include Accurate, Precise, Recall, and F-Measure, that are defined as follows.

$Accuracy$ = (TP + TN) / (TP + TN + FP +FN)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F-Measure = 2 x (precision x Recall) / (Precision + Recall)

Where TP, TN, FP, and FN stand for True Positives, False Positives, and True Negatives, respectively.

TABLE VII

COMPOSITION OF UCI DATASET (10299 INSTANCES)

% of Instances	Activity
18.50	Standing-up
17.25	Sitting-down

13.65	Climbling stairs down
14.99	Climbling stairs up
16.72	Walking
18.87	Lie down

The disarray lattice for this test, as well as the reviews (RCL), precisions (PRC), and F-Measure (FM) values for each class, are remembered for Table VIII. A most huge FPs and FNs are featured in striking language. Therefore, by and large precision is 92.5%.

TABLE VIII

THE CONFUSION MATRIX CONCERNING THE UCI DATASET TEST-SET.

	ACTIVITY	1	2	3	4	5	6	RCL	FM
1	Standing-up	0	2	0	86	444	0	0.83	0.85
2	Sitting-down	0	6	0	414	70	1	0.84	0.84
3	Climbing stairs down	0	1	419	0	0	0	0.99	0.96
4	Climbing stairs up	11	433	27	0	0	0	0.92	0.92
5	Walking	491	1	4	0	0	0	0.99	0.98
6	Lie down	0	27	0	0	0	510	0.95	0.97
	PRC	0.97	0.92	0.93	0.83	0.86	0.99		

The best performing pattern recognition design is picked when several supervised learning architectures are presented in these works. Our results are on line with current best practises. It might be claimed that the proposed network demonstrates excellent generalizability.

The dataset created using new data gathered with our equipment is displayed in Table IX.

TABLE IX

PIECE OF THE NEW DATASET (38764 INSTANCES)

% OF INSTANCES	ACTIVITY
11.7	Lie down
10.3	Climbing stairs down
11.7	Climbing stairs up
11.6	Stand
8.5	Running
20.6	Walking

10.6	Stay seated
7.1	Standing-up
7.9	Sitting-down

Comparing this dataset to the one used in the CNN architecture's optimization phase (Table III), it contains instances that are more evenly distributed, making it possible to examine the performance of our network more precisely.

The train set and testing set were created from this data and used to the third scenario previously indicated. Each user had three chances to finish the test; the initial and second times were for instruction, and the third time was for testing.
Overall reliability has been achieved at 97%.
Table X shows the disarray grid connected with this test-set. As already, the main misleading positive and bogus negatives are bolded. ID is the Action ID tracked down in Table I.

TABLE X
THE CONFUSION MATRIX RELATED TO THE TEST-SET

ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**RCL**	**FM**
1	1046	0	3	11	10	0	3	0	11	0.96	0.97
2	0	1328	0	0	0	2	25	4	1	0.97	0.97
3	5	1	1476	3	4	3	2	3	1	0.98	0.99
4	12	0	1	1270	15	0	0	0	21	0.96	0.96
5	8	0	1	8	1469	0	2	0	13	0.98	0.97
6	0	11	2	0	0	834	34	20	1	0.92	0.95
7	1	10	0	1	2	5	1452	5	4	0.98	0.98
8	0	16	5	2	1	13	11	963	1	0.95	0.96
9	0	0	1	17	17	1	17	0	2584	0.98	0.98
PRC	0.97	0.97	0.99	0.97	0.97	0.97	0.94	0.97	0.98		

When a fresh user needs to be tracked in our case, a light models with an automated feature extraction strategy is used to make training simpler. Additionally, there are fewer recognized activities (7 versus 6, respectively), which positively affects the outcomes. The hardware in is a smartphone, which is a suitable option for short-term monitoring (such as during a rehabilitation session), but these devices typically lack the ergonomics needed for continuous monitoring.

When a fresh user wants to be tracked in our case, a light models with an automated feature extraction strategy is used to make training simpler.

CONCLUSION AND FUTURE WORK:

This study suggests a special Internet of Things system for long-term, custom tracking of a person's behaviors at home. The gadget incorporates a Wi-Fi dressing sensor with profound preparation procedures to gather information on various exercises and recognize risky things to do. The strategy outlined here was created to be extended to systems that require several external sensors (such those present in homes with multiple occupants) and data delivery in a customized manner.

Deep Learning, like any Machine Learning methods, uses a lot of computational power to train the network, however using a pretrained network to do inference uses less processing power. Nowadays, graphics processing units (GPUs) are commonly employed to increase computing performance.

Due to their increasing variety and adaptability, we might consider employing embedded devices as an exciting alternative for the execution of the pre-trained CNN-based model.

The uncovered framework idea utilizes on-board Wi-Fi and distributed computing to continually add new preparation sets to the organization as new clients are added. The sensor sends each example of information it accumulates for these purposes to the cloud, which has been viewed as an energy-utilization issue. Power reserve funds can be accomplished by broadening information on the actual sensors, putting away them in neighborhood memory, and sending diminished information to the cloud. In the future, the CNN model described in this study on the sensor's reasoning phase might be used to significantly reduce battery consumption. The training stage has been intended to remain in the cloud because the system is only upgraded when a fresh user has to be added. This is because it typically demands the most processing resources.

The system architecture that was created paves the way for a different strategy that can make use of FPGA technologies to construct complicated signal processing systems in small, wearable, and self-sufficient embedded HAR systems.

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