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Research Article

Smart E-Health System for Heart Disease Detection Using Artificial Intelligence and Internet of Things Integrated Next-Generation Sensor Networks

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According to the World Health Organization, heart disease is the biggest cause of death worldwide. It may be possible to bring down the overall death rate of individuals if cardiovascular disease can be detected in its earlier stages. If the cardiac disease is detected at an earlier stage, there is a greater possibility that it may be successfully treated and managed under the guidance of a physician. Recent advances in areas such as the Internet of Things, cloud storage, and machine learning have given rise to renewed optimism over the capacity of technology to bring about a paradigm change on a global scale. At the bedside, the use of sensors to capture vital signs has grown increasingly commonplace in recent years. Patients are manually monitored using a monitor located at the patient's bedside; there is no automatic data processing taking place. These results, which came from an investigation of cardiovascular disease carried out across a large number of hospitals, have been used in the development of a protocol for the early, automated, and intelligent identification of heart disorders. The PASCAL data set is prepared by collecting data from different hospitals using the digital stethoscope. This data set is publicly available, and it is used by many researchers around the world in experimental work. The proposed strategy for doing research includes three steps. The first stage is known as the data collection phase, the data is collected using biosensors and IoT devices through wireless sensor networks. In the second step, all of the information pertaining to healthcare is uploaded to the cloud so that it may be analyzed. The last step in the process is training the model using data taken from already-existing medical records. Deep learning strategies are used in order to classify the sound that is produced by the heart. The deep CNN algorithm is used for sound feature extraction and classification. The PASCAL data set is essential to the functioning of the experimental environment. The deep CNN model is performing most accurately.

1. Introduction

The increasing proportion of people in their later years has made the provision of remote health monitoring an absolute need. In the field of health monitoring, recuperation, and supported living for the elderly and therapeutically tested folks, one of the most pressing challenges is maintaining consistent system administration between individuals, various pieces of medical equipment, and specialized organizations [1]. As a consequence of this, there is a need for wearable, low-control, inexpensive, and dependable medical technology that has the potential to enhance the quality of life of specific people who are afflicted with certain disorders. Additionally, it offers a potentially game-changing technical innovation that has the capacity to realize the aforementioned benefits in human services and increase healthcare administration structures. This advancement has the potential to realize the game-changing potential of technology. Internet of Things platforms that may be worn has the potential to be utilized in the remote gathering and transmission of data on a client and the area in which they are located. After then, the data may be evaluated and kept for use at a later time, if necessary. This sort of accessibility with external devices and services will either account for early prevention (for instance, after the prediction of an impending heart attack) or it will provide speedy treatment (for example, when a client tumbles down and needs assistance). In recent years, a great number of IoT frameworks have been developed for use in IoT applications that are associated with assisted living and medical services [2].

In recent decades, cardiovascular disease has supplanted all other causes of mortality to become the leading cause of death in the United States. It is quite challenging for medical professionals to make a correct diagnosis in a timely manner [3]. Because of this, the incorporation of computer expertise into this study is essential if it is to aid healthcare practitioners in providing timely and correct diagnoses. Figure 1 shows blocked arteries.

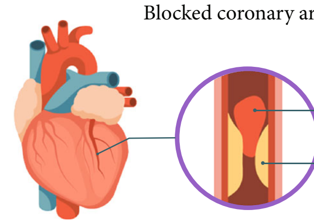

Figure 1: Blocked artery in a human heart.

Before these last few decades, heart disease was mostly seen as an issue that only older people faced. These days, however, it is well-acknowledged that it is one of the leading causes of mortality for individuals of all ages. It has been shown that India has a heart disease prevalence rate that is two times higher than the average for the rest of the world. In spite of the fact that heart disease is becoming more prevalent, a significant number of Indians continue to be ignorant of the symptoms that may accompany it. Even though having a history of heart disease in one's family is a significant risk factor in and of itself, the majority of heart-related disorders are caused by factors, such as high blood sugar, high cholesterol, high blood pressure, an unhealthy diet, smoking, a sedentary lifestyle, stress, and obesity. At this point in time, an individual's manner of life is the single most important factor in determining whether or not they will acquire heart disease [4].

One of the most promising technological therapies that are now developing to solve the global health equity gap is remote patient monitoring that is based on the Internet of Things (IoT) technology [5]. This specific kind of Internet of Things technology also goes by the term Internet of Medical Things (IoMT), which is an alternative moniker for IoT [6]. Throughout the whole of this dissertation, we are going to utilize the words "Internet of Things" and "Internet of Medical Things" interchangeably, despite the fact that our primary concentration will be on the medical sector. Thanks to IoMT technology, electrophysiological signals such as ECG, BP, SpO2, and glucose levels, in addition to user behaviors such as sitting, standing, and walking, may all be detected and remotely monitored in real time. This is a significant advancement. Utilizing automated decision support systems that take into consideration the data obtained from the many different monitoring indicators allows for early prognostication to be performed. This will be the beginning of a significant shift away from the conventional practice of diagnosing and treating illnesses toward a kind of health management that is more preventive in nature and is based on prediction [7].

The use of machine learning algorithms [8] makes it possible to unearth previously undiscovered information in the form of patterns hidden within the historical records of a database. A significant challenge for data mining systems is the capacity to correctly diagnose ailments in their early stages [9]. In order to arrive at an accurate diagnosis of a patient's condition, a great number of costly tests are required to investigate a diverse spectrum of symptoms as well as possible causes. On the other hand, data mining and machine learning algorithms could make it possible to significantly cut down on the number of patients who need to be tested. Because of this, the total number of necessary tests may be cut down, which has a favorable impact not only on the amount of time it takes to make predictions but also on the accuracy of such forecasts. Even though there are various data mining algorithms that are already being used in the healthcare industry, further research into the performance evaluation of such categorization techniques is required in order to get a higher level of precision in the results [10].

This article contains a smart e-health system for heart disease detection using artificial intelligence and the Internet of Things. Biosensor enabled stethoscope collects the heart sound of a patient. A wireless sensor network is used to connect all sensors and IoT devices. IoT devices establish a connection with a centralized cloud server, where all heart sound files are accumulated. Heart sound signal is separated from other noises using the blind source separation algorithm. The PASCAL data set is used to train and test the deep convolutional neural network.

2. Literature Survey

In 2016, Yeh proposed [11] the creation of a body sensor network (BSN) by the utilization of a platform that was driven by the Internet of Things (IoT). They proposed constructing two communication ways by utilizing sophisticated cryptoprimitives in order to safeguard the privacy of data transfers and authenticate entities inside a network of smart objects. These techniques would be used to authenticate entities. Both the central processing unit (CPU) and the backend BSN server belong to this category of approaches. The authentication of entities is the goal of both of these approaches. They have demonstrated that it is possible to carry out the method in the manner that is indicated by making use of the Raspberry PI platform. They have constructed an Internet of Things (IoT) testbed that is equipped with a number of different safety precautions. In this particular situation, the Raspberry Pi platform acts as a stand-in for a simulated LRU, which is another name for an intelligent moving object (LPU).

Heart rate sensor node analysis using embedded systems with assistance from Cogent Engineering was brought to light in 2017 by Fouad and Farouk [12]. Wellness, safety, recovery at the patient's home, assessment of the treatment's efficacy, and early sickness detection were all significant areas of focus.

Using a three-tier Internet of Things architecture and a machine learning algorithm, Kumar and Gandhi [13] developed a technique for the early identification of heart illness. This system was able to detect the disease in its earliest stages. They propose designs that are composed of three levels in order to store and handle the massive amounts of data that are created by wearable devices. This is done in order to make the data more manageable. The gathering of data is the primary objective of tier 1. The storage of massive amounts of data in the cloud is handled by tier 2 through the utilization of Apache FIBase. The development of a prediction model that is founded on logistic regression is carried out by tier 3 with the assistance of Apache Mahout. The utilization of ROC analysis ultimately results in the production of a nodal analysis of cardiac conditions.

In 2016, Park et al. [14] created a smart chair system that records and graphically portrays user posture by using a smartphone application. The goal of this system was to assist in the treatment of unequal posture. They sent data using low-power sensors such as pressure and tilt sensors, and they established connections using wireless technologies such as Bluetooth and iBeacons. Pressure and tilt sensors were two examples of these types of sensors. This Arduino implementation was done primarily with the goal of determining the various postures used by the user. This technique helps the user sit upright by recognizing their current situation and conveying that information in a manner that is simple to understand and aesthetically attractive via the use of an application on a smartphone. The graphic depicts a comparison between the user's actual posture and the ideal posture on both the left and right sides, with the amount of pressure represented by variously colored circles (red, yellow, green, and orange). This is an excellent example of how the Internet of Things technology may be put to use.

A study on the possible application of WSN technology in healthcare research to overcome challenges with patient monitoring was carried out by Alemdar and Ersoy [15]. The writers disseminated the information to a variety of subsets within the healthcare profession, such as those who deal with the chronically ill, the elderly, newborns, and youngsters whose parents are accountable for them.

Lai et al. [16] conducted an assessment of on-body sensor networks in order to compile a list of current developments and continuing challenges in a number of different disciplines. We also spoke about the many applications that the body sensor network may have. The authors hope that their in-depth study will be able to assist in fixing the problems that are still present with the existing frameworks.

In 1980, Sneha and Varshney [17] made the proposal that a framework should be developed for mobile-based patient monitoring. This framework's primary objective was to solve the issue of the high expenses associated with the underlying infrastructure of wireless sensor networks while simultaneously enhancing the communication channels that exist between patients and medical practitioners. The researchers contributed a variety of features and conceptual frameworks, such as those for power management and the design of systems. The many potential avenues of investigation served as the impetus for the research project.

Nigam et al. [18] presented a strategy to alleviate the lack of medical professionals in their paper that was published. The fundamental objective of the work that was planned was to send ECG sensor values through a remote connection. The provision of medical services was mostly limited to metropolitan regions. In addition to this, a cardiac report was compiled and forwarded to the experts for further examination.

The mobile health app was subjected to a comprehensive analysis that was supplied by Mosa et al. [19]. Following an examination of more than 2800 academic publications, a total of 88 potential applications in the medical field were discovered. These programs have been put to a wide variety of purposes, some of which include the provision of drug recommendations, health monitoring calculators, communication tools, databases of medical institutions, and tools for the diagnosis of illnesses. Additionally, the authors note the ubiquitous availability of smartphones as well as their potential usefulness as a tool for remote monitoring.

Appelboom et al. [20] conducted research not too long ago in which they collected data on the development of smart wearable biosensors as well as the clinical effectiveness of these biosensors. This review was collected by making use of a broad range of methodological domains, some of which include but are not limited to connected devices, biosensors, telemonitoring, wireless technologies, real-time home observation equipment, and so on. According to the findings of the study, the use of sensors in the healthcare industry was both beneficial and dependable. In addition, the sensors' full capabilities were not used in any way.

Neves et al. [21] investigated the use of wireless sensors in healthcare promotion because of the unique qualities that they have, such as low-cost data processing, availability, growth, and other similar attributes. The wireless sensors network was at first only available to members of the armed forces, but it was subsequently opened up to members of the civilian sector as well. According to the findings of the study, biosensors are an effective method for monitoring a broad range of diseases. In addition, some challenges connected with the adoption of WSNs in healthcare settings were investigated.

The capabilities of the wearable gadget were improved by Azariadi et al. [22] so that the researchers could have a better knowledge of the electrocardiogram data and the heartbeat. The utilization of wearable technology has shown to be extremely beneficial to the research and development of monitoring tools that are more effective for a variety of subfields within the healthcare business. The ECV and the patient's average heart rate during the previous twenty-four hours are both taken into consideration when making a diagnosis with the use of this diagnostic tool, which was intended to aid medical professionals in the diagnosis of patients. It is now more important than ever to monitor patients remotely so that healthcare providers may serve patients who are located in a range of places while also lowering their costs.

3. Methods

This section contains a smart e-health system for heart disease detection using artificial intelligence and the Internet of Things. Biosensor enabled stethoscope collects the heart sound of a patient. A wireless sensor network is used to connect all sensors and IoT devices. IoT devices establish a connection with acentralized cloud server, where all heart sound files are accumulated. Heart sound signals are separated from other noises using the blind source separation algorithm. PASCAL data set is used to train and test the deep convolutional neural network. Figure 2 shows a smart e-health system for heart disease detection using artificial intelligence and the Internet of Things.

The continual monitoring of patients' health, as well as their fitness levels and activities, can be greatly aided by the utilization of wearable sensor technologies [16]. There is an ongoing process of conserving the data that is created by this illness in order to assist patients with a broad variety of medical therapies and to enhance the overall health of the community as a whole. This is done to help combat the effects of the illness. Reliable health data may also be utilized in the process of defining daily norms and conducting physical examinations on the individual. Many of the gadgets that are connected to the Internet of Things (IoT) are created with the purpose of monitoring a person's vital signs, such as their blood pressure, heart rate, blood sugar levels, and level of pain. These monitors, which are surgically placed within the patient's body, keep track of the subject's vital signs at all times throughout the experiment.

The phrase "wireless sensor network" (WSN) refers to a system that functions at a distance and is made up of widely dispersed, autonomous devices that employ sensors to monitor environmental or physical parameters. This kind of network is also known as a "distributed sensor network." These independent nodes, which are sometimes referred to as hubs on occasion, are part of what makes up a WSN system [15] together with switches and a conduit. Sensor systems are the means by which the data required by smart circumstances may be socially distributed. This is true regardless of whether the smart situation is in a building, a utility, a company, a house, a ship, or the automation of transportation infrastructure. We need adaptive sensor systems that are able to expand and be configured in order to battle contemporary psychological oppressors and guerrilla fighters. In these kinds of environments, installing wiring or cable is often impractical. We need a sensor network that is simple in both its installation and its ongoing maintenance. It is the intention of the illuminating paragraph to make internet-based communication between WSNs and open-source networking technologies easier to do.

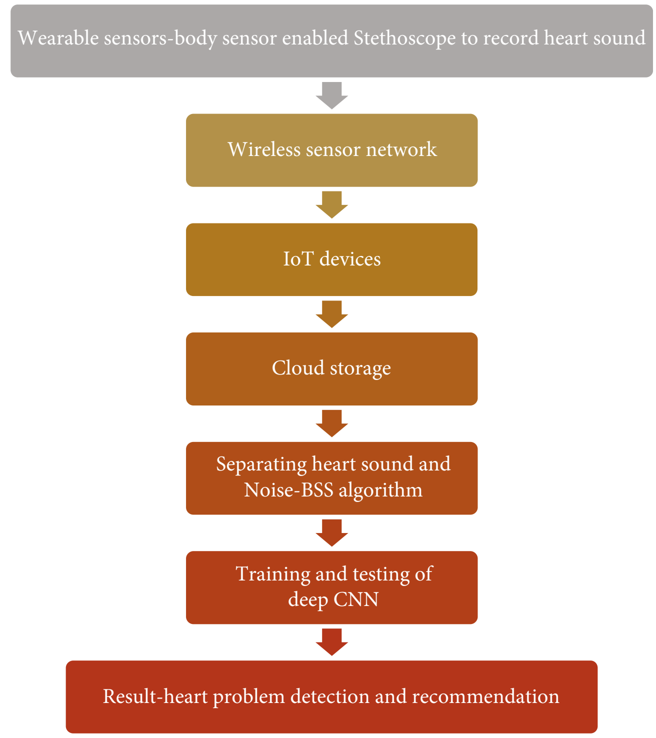

Figure 2: Smart e-health system for heart disease detection using artificial intelligence and the Internet of Things.

Since of this, cloud computing [13] is an essential enabler for e-health frameworks because it can provide the computational and storage infrastructure that is required to tackle the issue of e-health information management. As a result, caregivers have the opportunity to use this data to their benefit by redistributing it to a different cloud service. That not only relieves them of a load of maintaining and keeping the data up-to-date in a way that is both effective and cost-effective for them.

It is very challenging to reassemble a whole audio signal from a corrupted observation. Separating HSS from the ambient noise is one of the obstacles that must be overcome. Blind source separation is one of the solutions that may be applied to this issue, which is one of many possible approaches. The sensor array is part of a BSS that is considered to be the most critical. Beam creation by using the multisignal data from an array of sensors is an integral part of BSS [23]. The beam former is responsible for collecting signals from several sources in order to provide guided reaction. The signal of interest sees an improvement as a result of the interference from irrelevant sources being cut down significantly [24]. These BSS algorithms get their start from the fundamental ideas of independent component analysis (ICA), which serves as their foundation. In contrast, ICA has the ability to handle mixed signals in real time. One may be able to make inferences by making use of the pattern in the arrival time of the source that is formed by the separation matrix.

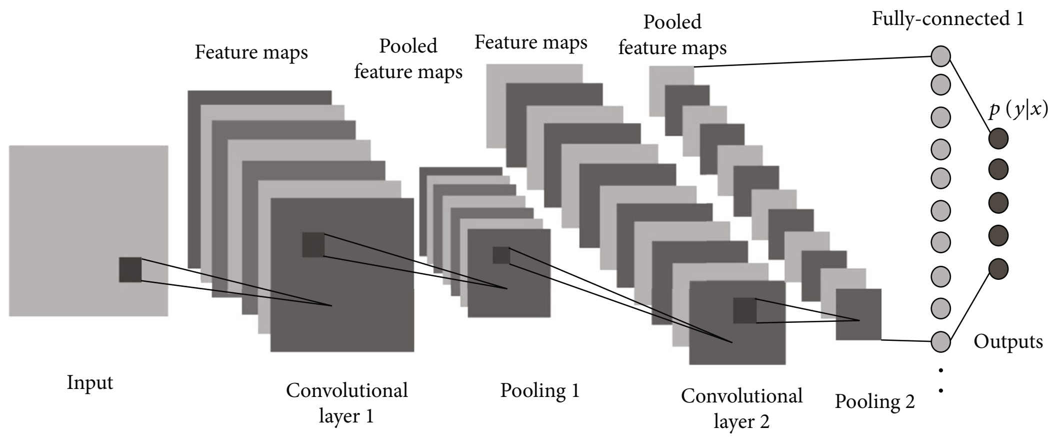

Figure 3: Architecture of deep CNN model.

The deep convolutional neural network is one of the most cutting-edge AI approaches, and it was designed specifically to solve difficult issues that arise in computer vision (Deep CNN). Deep CNN, a kind of deep learning that is represented by a feed-forward artificial neural network, has been employed in a number of articles dealing with the classification of agricultural photographs. These works may be found in the following: Important to Deep CNN are the layers known as convolutional layers, which use filters to extract properties from the photos that are sent into the network. It is possible that increasing the total quantity of training data might make deep CNN even more successful. One of the most significant benefits of using deep CNN for image classification is that it might drastically cut down on the amount of feature engineering that is required.

The deep CNN network is comprised of numerous layers, each of which is responsible for a separate convolution. An illustration of the layered architecture that may be achieved using the deep CNN approach is shown in Figure 3.

Each layer of the network creates a new representation of the training data, with the representations that are more general appearing in the outermost layers and the representations that are more particular going deeper into the network. The dimensionality of the training data is decreased by the convolutional layers, which work as feature extractors, and the pooling layers, which are responsible for the reduction in the number of dimensions. Convolutional layers are layers that take low-level inputs and turn it into higher-level properties that may be utilized for categorization. One further thing to keep in mind is that the convolutional layers are the essential component of any deep CNN system.

The process of feature engineering is what differentiates deep learning from other, more traditional types of machine learning. The pooling layer is responsible for the process of downsampling that takes place in the spatial dimension. It contributes to reducing the overall number of options available. The method known as maxpooling is implemented in the pooling layer of the recommended model. Maximum pooling performs better than average pooling in the deep CNN model that was presented. The process of removing nodes from a network is an additional layer that plays an important part in the overall structure. It is a kind of regularization that is used to reduce the effects of overfitting. The next layer, known as the dense layer, is responsible for classification. This layer gets input from the convolutional and pooling layers that came before it. Deep CNN involves a significant amount of iteration in addition to the training of several models in order to arrive at the best possible result. The basic optimization method known as gradient descent, which is often referred to as batch gradient descent, is used in gradient descent. In this approach, the gradient steps are carried out using full training data on each step. When dealing with a large training set, the gradient descent algorithm may be difficult to implement.

4. Results Analysis and Discussion

PASCAL data set [25] contains heart sound samples. It has 449 records and five classes. The classes are normal, noisy normal, extrasystole, murmur, and noisy murmur. Heart sound signals are separated from other noises using the blind source separation algorithm. PASCAL data set is used to train and test the deep convolutional neural network. 300 images are used to train the deep CNN model, and 149 images are used to test the CNN model. The results are shown in Figure 4. Different parameters are used to observe the performance of deep CNN and compare the results of deep CNN with other classification models support vector machine, ANN, and logistic regression. Framework was implemented in the Jupyter tool. It is a Python-based tool. I5 7th generation processor with 3.2 GHz with 8GB RAM was used in the experimental setup.

From Figure 4, it is clear that the accuracy of deep CNN is 98.4 percent. It is higher than the SVM, LR, and ANN algorithms. Also, the precision of deep CNN is 99 percent, which is 2.6 percent more than the precision of an ANN algorithm. Recall and the F1 score of deep CNN are also higher than other classifiers used in the experimental work.

The most essential performance measurements are the classification accuracy score, the precision score, the recall score, and the F1 score [26, 27]. It is common practice to use a confusion matrix in order to demonstrate how well the models perform on the test data. A confusion matrix is

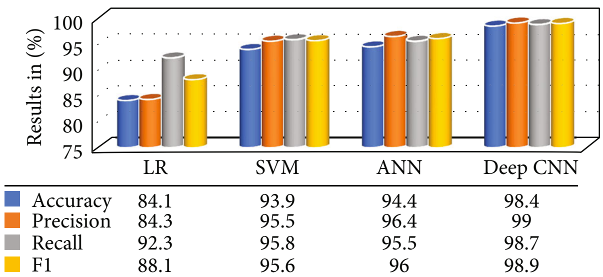

Figure 4: Performance analysis of deep CNN model on PASCAL data set.

Table 1: Confusion matrix of machine learning algorithms.

Parameter	Deep CNN	ANN	SVM	Logistic regression
TP	310	300	297	265
TN	132	124	125	113
FP	3	11	14	49
FN	4	14	13	22

a useful tool that may be used to provide a visual representation of the efficacy of various machine-learning approaches. The confusion matrix takes into account four different values: true positive (TP), false negative (FN), true negative (TN), and false positive (FP). It is shown in Table 1.

The accuracy of a classification method may be evaluated based on the percentage of a given group of test files that have been correctly assigned to their respective categories.

The total number of occurrences in which the model properly classified the data as positive is referred to as the true positive. If a number is described as true negative, it means that it has been unequivocally established as having a value that is in the negative range. To elaborate, a false positive is the occurrence of a false positive classification when the underlying data is negative. This is referred to as a false positive classification. A false positive is often referred to as a type 1 error. A false negative is a number that has been incorrectly labelled as having a negative value, regardless matter how much time it takes to arrive at that conclusion. This phenomenon also goes by the name of the type 2 error, which is also often referred to as the false negative. These parameters are what define the classification accuracy, precision, recall, and F1 score of deep convolutional neural networks and other contemporary machine learning and transfer learning methodologies.

5. Conclusion

Diseases of the heart are the leading cause of mortality on a global scale. If cardiovascular illness can be recognised in its early stages, it may be feasible to reduce the total mortality rate of people. If a heart condition is diagnosed at an earlier stage, there is a larger likelihood that it may be effectively treated and managed under the direction of a physician. This is especially true if the disease is detected earlier in its progression. Recent developments in fields like the Internet of Things, cloud storage, and machine learning have sparked a rekindled sense of optimism over the potential for technology to usher in a paradigm shift on a global scale. This article includes a cutting-edge e-health system that uses both artificial intelligence and the Internet of Things to detect heart disease in patients. The patient's heart sound is collected via a stethoscope equipped with biosensors. In order to link all of the sensors and other IoT devices, a wireless sensor network is used. Internet of Things (IoT) devices create a link with a centralized cloud server, which is where all of the heart sound recordings are gathered. Using the blind source separation technique, the heart sound signal is isolated from the surrounding background noise. In order to train and validate the deep convolutional neural network, the PASCAL data set is used. When training the deep CNN model, 300 photos are utilized, but just 149 images are used when testing the CNN model. Several distinct factors are used in order to evaluate how well deep CNN performs in comparison to other classification models and to monitor the performance of deep CNN itself. Logistic regression, support vector machine, and artificial neural networks deep CNN are doing much better than other models across all parameters.

Data Availability

Data shall be made available on request from the corresponding author.

Conflicts of Interest

All authors declare that they do not have any conflict of interest.

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