An Architecture for Cloud-Assisted Clinical Support System for Patient Monitoring and Disease Detection In Mobile Environments

Cornelius C. Agbo
Department of Electrical, Computer and Software Engineering
University of Ontario Institute of Technology
Oshawa, Ontario, Canada
cornelius.agbo@uoit.net

Qusay H. Mahmoud
Department of Electrical, Computer and Software Engineering
University of Ontario Institute of Technology
Oshawa, Ontario, Canada
qusay.mahmoud.uoit.ca

J. Mikael Eklund
Department of Electrical, Computer and Software Engineering
University of Ontario Institute of Technology
Oshawa, Ontario, Canada
mikael.eklund@uoit.ca

ABSTRACT

Opportunities exist to improve healthcare delivery by extending to the domain of mobile healthcare the emerging clinical support system that facilitates patient monitoring and early disease detection. Current research focuses on hospital-level patient monitoring using an automated clinical support system. A similar system can be adapted to support medical monitoring and remote care for mobile patients. Unlike the hospital environment where stationary computing infrastructures can be leveraged for the medical data acquisition, processing and storage, the mobile healthcare environment may rely solely on mobile devices, such as a smartphone, to acquire and process the medical data. Given that the mobile devices are constrained by energy, processing and storage capabilities, outsourcing some of the operations to the cloud is a plausible approach. Cloud-assisted clinical support system for mobile patients creates more opportunities for healthcare delivery, but there are attendant challenges that must be considered in the development of the system. This paper identifies these opportunities and the challenges that exist with the development of cloud-assisted clinical support system for patient monitoring and disease detection in mobile environments, and introduces an architecture for developing the system, with a proof of concept.

KEYWORDS

Mobile healthcare; disease detection; patient monitoring; clinical support system; arrhythmia detection; physiological data, ECG analysis; heartbeat detection.

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1 INTRODUCTION

Clinical research has shown that it is possible to detect the onset of certain diseases or other clinical conditions by analyzing the physiological data of the affected patients [1, 15]. Therefore, it has become a standard clinical practice to continuously monitor and analyse the physiological data of patients to detect patterns that may correlate to a given clinical condition. Manual analysis of these physiological data streams is non-trivial, given the volume and the variety of the physiological data that are involved, and the velocity at which the medical devices produce them. For example, the electrocardiogram (ECG) signal displayed on bedside medical monitors are constructed from physiological data streams that are produced at rates that sometimes exceed 1000 samples per second [11]. In addition, manual analysis of the physiological data is prone to human error due to fatigue or other factors.

Since it is difficult to manually analyse the high-frequency physiological data streams, information technology sysems and software are utilized to build clinical (decision) support systems (CSSs), that assist healthcare providers in making sense of the phsyiological data [1, 3]. A typical clinical support system acquires the physiological data from the medical devices connected to a patient and analyses them, usually in real-time, using a set of known clinical rules, [1] for early detection of diseases or other clinical conditions. CSSs also provides a persistent storage of the acquired physiological data and the results of the analysis for future reference or further analysis. Some CSSs incorporate complex data mining algorithms for advanced clinical research [1].

Evidently, running CSS requires high computational and storage resources for timely execution of the complex data analytics algorithms and for the storage of the high-volume physiological data respectively. Cloud computing offers the best advantage for provisioning these computational and storage resources, hence, cloud-based CSS is proposed as a viable solution and have been deployed in different hospitals [9, 15, 19]. The ongoing research in this domain focuses on

[1] Clinical rules are specifications of patterns which when exhibited in the behaviour of physiological data streams of a patient are indicative of an impending clinical condition.

hospital-level monitoring, i.e., for patients that are admitted in the hospital.

There is the potential to enable the extension of hospital-level medical monitoring and clinical support to patients at home and even allow for patient mobility outside the home through the integration of mHealth with the cloud-assisted CSS. Mobile healthcare, also known as mHealth is the healthcare practice involving the use of mobile devices, such as smartphones and tablets, to achieve various healthcare objectives [7, 14]. mHealth offers the opportunity to make the cloud-assisted health monitoring services and support accessible to at-home and mobile patients.

However, mobile healthcare environment, unlike hospital environment, does not have access to stationary medical devices and computing systems for the acquisition and transmission of the physiological data to the cloud. Instead, mobile patients may rely solely on their mobile devices for the acquisition, pre-processing and transmission of the physiological data to the cloud. These mobile devices have limited resources and battery life. In addition, the mobility of the patient in mHealth makes it more difficult to achieve stable network connection between the mobile device and the cloud. These differences account for a new set of challenges. In this paper, we identify and briefly discuss the opportunities and the challenges that exist with the development of the cloud-assisted clinical support system for patient monitoring and disease detection in mHealth, and introduce an architectural approach for the development of the system, with a proof of concept.

The remainder of this paper is, therefore, organized as follows. Section 2 presents a review of the related work. Section 3 briefly discusses the opportunities and the challenges that exist with the development of the cloud-assisted CSS for mHealth. In Section 4, we describe the proposed architecture for cloud-assisted CSS for mHealth. Section 5 presents a proof of concept for the proposed architecture. Section 6 concludes the paper and offers ideas for future work.

2 RELATED WORK

The Artemis platform [1] is a good example of a hospital-level clinical support system which was developed for monitoring and detecting the clinical conditions that affect patients admitted in critical care units (CCUs)of hospitals. Originally, Artemis was developed as an in-house system, with all its componets located within the hospital premise. Later work extended the Artemis platform to the Artemis Cloud [9, 15] using cloud computing software-as-a-service and data-as-a-service models. The patients' physiological data are acquired with the help of hospital-based medical sensor devices that constitute the data acquisition component of Artemis. Artemis also has a clinical information system (CIS) component, which is the electronic record of the patients, from where other relevant health data may be collected to enrich the physiological data for the analysis.

In the architecture of the Artemis Cloud, the CIS component and, of course, the data acquisition component are located in the hospital, where the monitored patient is admitted. The component of the Artemis that analyses the physiological data is hosted in the cloud, as software-as-a-service, together with a storage module for persistent storage of the acquired physiological data. Another component of Artemis that is hosted in the cloud is the data mining component, which is used to, retrospectively, analyse the persisted data for further insights, in advanced clinical research. The health data of a monitored patient are collected at the hospital and transmitted to the cloud, through a high-speed Internet connection, where they are analysed to support clinical decision making. Several deployments of Artemis Cloud [9–11, 15, 19] have focused on hospital-level patient monitoring, in particular, critical care patients admitted to the CCU.

Like the Artemis cloud, most other works in the literature, such as [5, 16], on the use of computing and cloud technologies for remote clinical support and patient monitoring focus only on patients admitted in a hospital, i.e., patients within the hosptial environment where there is access to stationary medical devices and computing systems. Research is currently lacking on the application of cloud-based CSS for patient monitoring and disease detection in an mHealth environment. Most mobile solutions to-date are focused on discrete measurements, e.g. [4]

Mobile patients, unlike stationary patients, do not have access to stationary medical devices and computing resources. Instead, they rely on wearable medical devices and body area sensors for data acquisition and utilizes mobile devices, such as smartphones, for data processing [6]. This limitation, coupled with the mobility of patients in mHealth account for a set of challenges that must be considered in the development of clinical support system for mobile patients. To underscore the motivation for this research, we precede the discussion of the challenges with the opportunities that are offered by the development of a patient monitoring and disease detection system for mobile and at-home patients.

3 OPPORTUNITIES AND CHALLENGES

The development of the cloud-assisted clinical support system to facilitate real-time patient monitoring and early disease detection for mobile patients offers some new opportunities for healthcare delivery, but also introduces some challenges that need be addressed. In this section, we briefly discuss these opportunities and challenges that are inherent in the cloud-assisted CSS for mHealth.

3.1 Opportunities

3.1.1 Extension of CCU-levels of monitoring and support to home and mobile environment. As previously noted, CSS, such as the Artemis, was designed and developed to monitor and offer clinical decision support for patients in CCU, which is the department in the hospital that caters to the critically ill patients, mostly children and the elderly. Developing the cloud-assisted CSS for mHealth offers the opportunity to extend the CCU-levels of monitoring and support to other patient groups, such as at-home and mobile patients. This also paves the way for the early detection of other clinical conditions, other than those that affect critical care patients.

3.1.2 Reduction in the length of hospital stays and healthcare cost.
For the patients admitted to the hospital, the possibility of at-home monitoring through mHealth could potentially reduce the length of hospital stay and the healthcare cost.

3.1.3 Access to pre-admission physiological data.
The development of cloud-assisted CSS for mHealth, where a patient's physiological data can be collected through body area sensors and transmitted to the cloud storage with the help of a mobile device, makes it possible for the clinicians to have access to the physiological data of the patient before the patient is admitted to the hospital. This facilitates early and accurate diagnosis.

3.1.4 Can potentially reduce accidents and mortality for epileptic patients.
Development of CSS for mHealth can assist epileptic patients to detect an impending epileptic seizure before its onset. This can potentially save the patient from an accident or even death by giving the patient the opportunity to position oneself in a safe environment before the onset of the seizure.

3.2 Challenges

3.2.1 Security and Privacy.
The security and privacy issues involved in the transmission of healthcare data to the cloud are well understood. Healthcare data are very sensitive and their security is of paramount importance. Similarly, the identity and privacy of a patient must be protected as the patient's data are trasmitted to and from the cloud. However, these challenges are not peculiar to mHealth. Earlier works, such as the Artemis Cloud [15], have proffered solutions on how to protect a patient's privacy and the integrity of the medical data. The use of private cloud, virtual private network (VPN), and various secure and privacy-preserving encryption schemes, are all good measures that achieve considerable data security and privacy in the cloud. However, some of these measures require fixed infrastructures and heavy computation which are not always available in an mHealth environment.

3.2.2 Real-time Response.
How to detect a medical condition and deliver an alert to the user in near real-time is yet another challenge in the cloud-assisted CSS for mHealth. The system must respond in near real-time to enable the user to detect an impending clinical condition before its onset. In a cloud-assisted CSS, care must be taken to ensure that the response time of the system is not adversely affected by the added communication delay between the cloud and the mobile terminal. This is more so in an environment where the mobile patient may move to an area without a stable Internet connection.

3.2.3 Communication and Interoperability.
As earlier noted, achieving reliable and stable network connection between the mobile devices and the cloud is not always possible. The large volume of the patient's data to be transmitted requires stable, reliable and fast Internet connection, and this is difficult to achieve in an mHealth environment. Dealing with this challenge is an important aspect of the development of the cloud-assisted CSS for mHealth. Another challenge is how to achieve synchronization and interoperability among different mobile devices in a multi-vendor, multi-tenant cloud environment without incurring unacceptable performance degradation.

3.2.4 Certification and Trust.
To facilitate the adoption of the cloud-assisted CSS for mHealth, there is the need to build trust and confidence in the stakeholders - the clinicians, the patients, and the regulatory authorities. Trust mechanism is usually achieved through certification. Certifying a cloud-based application is challenging because it is difficult to convince stakeholders that a piece of software application running somewhere in the cloud, in an unknown location, in an unknown hardware, together with other unknown software works correctly and securely, in accordance with the specifications. How do you convince a clinician or patient to trust the judgement of a remote application when he or she receives an alert indicating an impending clinical condition?

4 PROPOSED ARCHITECTURE

In this section, we describe the cloud-assisted architecture that is proposed to realize the above-mentioned opportunities while it overcomes the identified challenges. The main functions of the CSS in this case are two folds: (1) to provide near real-time analysis of a patient's physiological data streams to alert the patient or a clinician of any impeding medical condition, and (2) to allow for the storage of the physiological data for future use or further analysis. The analysis that is done on previously stored data is often referred to as offline analysis, in contrast to online analysis which is applied to real-time or streaming data. It therefore follows that the functions of CSS consist in performing the online and the offline analysis of a patient's physiological data. The offline analysis is usually more sophisticated or complex and can be used to gain better insights into the behaviour of the physiological data or to validate the result of the online analysis. In our proposed architecture, the data storage and the offline analysis of the data are outsourced to the cloud, whereas the online analysis of the physiological data for real-time insight are run within the mobile device. The resulting cloud-assisted architecture of a clinical support system is depicted in Figure 1.

As the diagram shows, the physiological data is streamed from the body area sensors through an embedded lightweight physiological data acquisition module. An example of such physiological data acquisition module is the e-Health Sensor Platform by Cooking Hacks [8]. This kind of platform can collect different physiological data, such as oxygen saturation (SpO2), blood pressure (BP), electrocardiogram (ECG), heart rate (HR), and electroencephalogram (EEG), from the medical sensors which are connected to the patient, and perform some pre-processing functions, such as filtering and encoding, on the received data. The data from this module

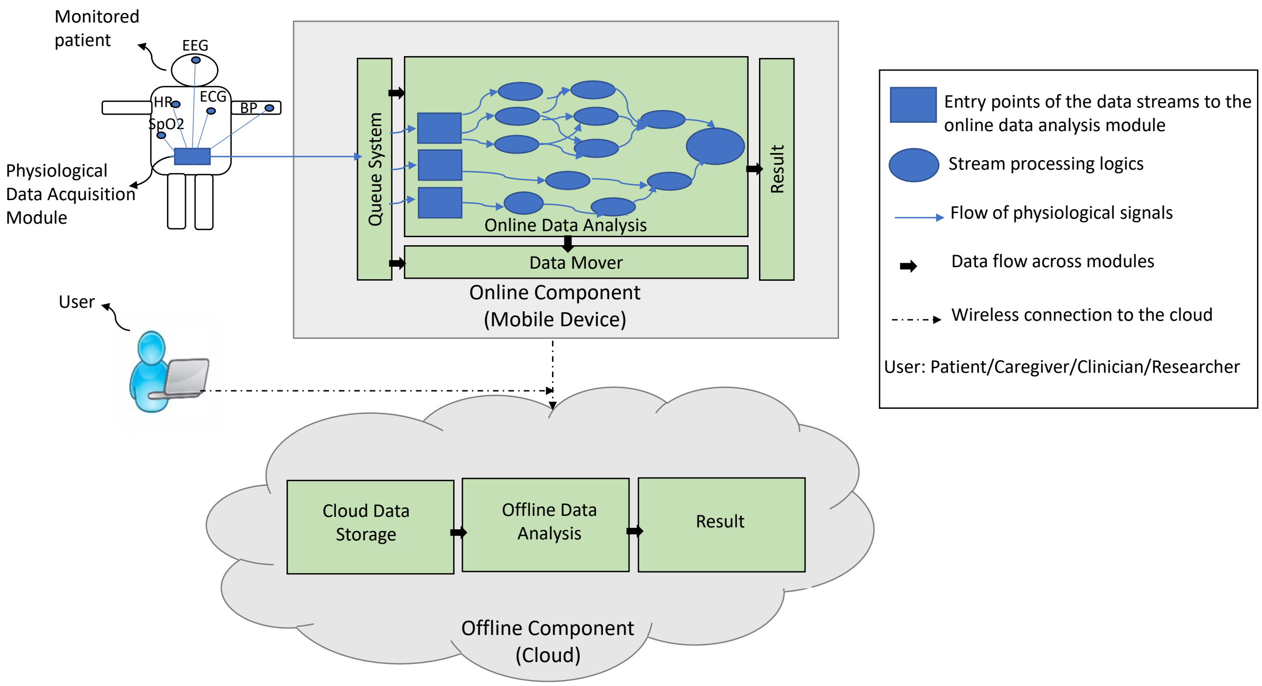

Figure 1: Proposed architecture

are then sent to the mobile device where the online analysis takes place.

The mobile device component is made up of interconnected application modules as can be seen in the diagram. The Queue System serves as a messaging application that receives the physiological data as they are streamed from the data acquisition module, stores them temporarily and pace their transmission to the data analysis module. As the data move from the queue system through the online data analysis module, they are analyzed to derive any useful insights.

The Online Data Analysis module analyzes the physiological data streams for early detection of diseases or other clinical conditions. To reduce the computational load on the mobile device, this module runs only simple algorithms that are computationally inexpensive, to derive some real-time insights from the streaming physiological data. The presence of anomalies in the result of the real-time analysis is used to predict or detect any relevant condition of interest. The result of the online analysis does not necessarily have to be conclusive, but may be indicative of a need for further diagnosis. The online analysis is run on a mobile device, or on a home computer for an at-home patient. It's necessary to localize the online analysis within the patient's environment to achieve near real-time response by avoiding the additional round-trip delay that would be incurred if the online analysis were to be outsourced to the cloud. This also mitigates the challenges that could potentially arise due to failures in the communication link between the mobile device and the cloud in an mHealth environment.

The Data Mover module coordinates the transmission of the raw data of the patients to the cloud for persistent storage. When there is network connection failure, the data mover may store the incoming physiological data locally until connection is restored or discard the data if the memory capacity of the mobile device is exceeded. If an anomaly is detected in the online analysis, an alert is triggered through the Result module to let the patient take the necessary action, such as calling the emergency service, or in the case of an epileptic patient, to safely position oneself before the seizure occurs. Where it is needed to provide telemetry monitoring of the mobile patient, an alert resulting from the online analysis is automatically transmitted to a remote monitor through the data mover, but this too is subject to possible connection failures and data loss.

The main function of the cloud in this architecture is to persist the data from the online component for further analysis. During the operation of the CSS, the streaming physiological data are transmitted to the cloud where they may be subjected to further analysis, using more complex data mining algorithms. The results of the offline data analysis on the cloud can be visualized through the cloud-based Result module, which is usually a web interface. A user is able to make a wireless connection to the cloud to utilize the stored data for various purposes. The system user could be the patient or the patient's caregiver. The user could also be a clinician or a researcher performing offline analysis on a patient's data or conducting clinical research on the persistently stored physiological data, respectively.

The blue arrows in the diagram are used to depict the flow of the physiological data streams through the system. The blue rectangles denote the entry points of the data streams into the Online Data Analysis module. The circular shaped blue objects represent the processing logics that are involved in the data transformation and analysis. The short big arrows show the movement of data across modules, while the dotted arrow depicts the wireless communication link from the mobile device or the user to the cloud.

An interesting feature of this architecture is the splitting of the clinical support system into two components: the online component, consisting of early disease detection, which runs locally on the mobile device and the offline component, consisting of persistent storage and offline analysis, which is offloaded to the cloud. This architecture has an obvious advantage over outsourcing of the entire CSS functions to the cloud, like in Artemis Cloud. In hospital-level monitoring or in an environment with strong and reliable Internet connection, it may be possible to outsource the entire CSS operations to the cloud; in which case, the local device is only used for data acquisition and transmission. For a mobile environment, however, it is more practicable to have the online component localized on the mobile device to achieve a measured response time for the real-time patient monitoring and disease detection. This is because in a mobile environment, stable Internet connection to the cloud cannot be guaranteed. If the online component is outsourced to the cloud, the system's response time becomes unpredictable, which makes it unsuitable for real-time applications. By localizing the online component on the mobile device, we ensure that the response time of the system during online analysis is unaffected by the variable round-trip delays and possible data loss that could arise from intermittent losses of network connection which characterize the mobile environment.

It should also be noted that, in contrast to Artemis Cloud, the mHealth architecture does not have access to the patient's electronic health record (EHR)locally on the mobile device; therefore, the mHealth patient monitoring architecture is only applicable to diseases that can be detected with only the physiological data. Other patient monitoring applications requiring EHR can be run from the cloud-based module, where the EHR is integrated in the cloud-based storage module, but real-time response may not be guaranteed.

In what follows, we present a proof of concept using an example of a simple patient monitoring and disease detection application based on ECG analysis.

5 PROOF OF CONCEPT CASE STUDY

A proof of concept is used to demonstrate that a design concept is feasible. To illustrates how the proposed architecture can be used to feasibly develop a patient monitoring application, let us consider an example of an aged patient who

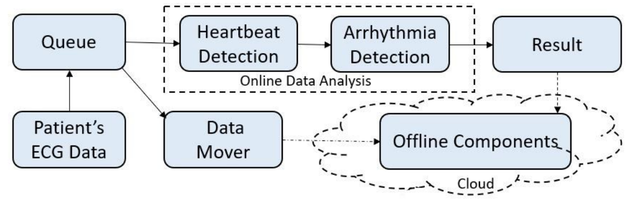

Figure 2: Arrhythmia detection system

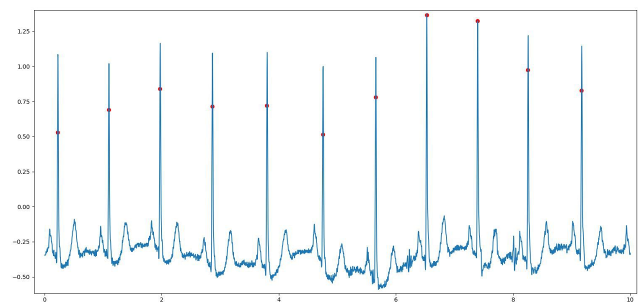

Figure 3: Plot of record 101 showing the detected heartbeats

is prone to arrhythmia (irregular heartbeats). We describe a design and a preliminary implementation of a monitoring application for this patient and the detection of arrhythmia based on the proposed architecture.

Arrhythmia is a medical condition associated with abnormal heart rhythm [2]. There are different types of arrhythmia, such as bradycardia, tachycardia, and premature ventricular contraction (PVC). There are different methods and algorithms that can be applied to detect any of these types of arrhythmia. However, there is a simple arrythmia detection method, presented in [18], in which heart rates below 60 and above 100 BPM (beats per minute) are considered abnormal for humans, and therefore indicative of arrhythmia. This method is simplistic, and would require a more reliable arrhythmia detection technique to be validated and to properly classify the nature and type of the arrhythmia.

However, we can use this method for the proof of concept. Using our architecture, this simplistic arrhythmia detection method can be implemented on the mobile device, while a more complete detection method is implemented on the offline cloud component. Consider a scenario where an elderly patient at home is monitored for arrhythmia. We can utilize a lightweight medical sensor device, such as the one discussed earlier, to record the patient's ECG reading and store them temporarily on the queue system that uses the mobile device memory. From the queue system, the ECG data are feed into the online data analysis module where they are analysed to get a real-time insight on the arrhythmia status of the patient using the simple detection method. At the same time, the queued data are also removed from the mobile device to free the memory space by transmitting them to the cloud, or discarding them entirely, if there is no network connection to the cloud module, maybe due to network failure. At the cloud side, the data may be further analysed, this time, using more advanced algorithms to properly classify the nature and type of the arrhythmia.

The arrhythmia detection system described above is depicted in Figure 2. The online data analysis component is composed of two processing stages. The first stage consists in detecting the number of heartbeats in a segment of the ECG data. Based on the number of detected heartbeats and the duration of the ECG segment, the second stage determines the patient's arrhythmia status by calculating the heart rate in beats per minute and comparing this value with the normal range of 60 - 100 BPM. If the heart rate is found to fall outside this range, then the patient is alerted through the result module of the likelihood of arrhythmia. Further analysis may then be conducted based on the ECG data that have been persisted in the cloud to validate the result of the online analysis and to further classify the nature of the arrhythmia.

As a preliminary work, the online data analysis component of the arrythmia detection system has been implemented using the heartbeat detection algorithm based on New Nonlinear Transformation and First-Order Gaussian Differentiator [12]. This algorithm has been tested with the ECG data from the PhsioBank MIT-BIH arrhythmia database [13, 17]. As shown in Figure 3, the implemented algorithm accurately detects the 11 beats on the first 10-seconds segment of record 101 of the MIT-BIH database. Since there are 60 seconds in 1 minute, then we can easily compute the heart rate in BPM on a segment of 10 seconds by multiplying the number of beats in the segment by 6. In this case, the heart rate of the patient who has the record 101, based on the first 10-seconds segment, is 66 beats per minute (6*11). Since 66 is between 60 and 100, we consider the patient's heart rhythm to be normal. By continuously monitoring the heart rate, the system can detect and report any abnormal change in the patient's heart rhythm (arrhythmia).

6 CONCLUSION AND FUTURE WORK

In this paper, we have presented the state-of-the-art in the research on cloud-assisted clinical support system for hospital-level patient monitoring and disease detection. We have discussed how the development of similar system for mHealth will improve healthcare delivery by extending real-time monitoring and early disease detection to patients outside the hospital. We have also discussed the challenges that the development of such system faces and proposed an architecture that could mitigate some of these challenges. We have also shown a proof of concept, using an example of the detection of arrhythmia.

The limitation of the mHealth architecture which we have proposed is that it does not integrate electronic health record in the online analysis. Therefore, real-time patient monitoring is only supported for cases where only the physiological data are sufficient to detect the medical condition. In addition, there is the need to develop more lightweight security and privacy-preserving solutions, as most of the solutions used for hospital-level monitoring are not suitable for mHealth applications for the reason of the resource constraints in mHealth environments.

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