

A Lambda Architecture for Imbalance Prediction With Smart Cane

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Abstract : Providing medical staff with a system for imbalance prediction can be a way to track frailty and to monitor patient's state more accurately, since imbalance is assessed as a warning sign of frailty. The purpose of this paper is to propose a complete architecture able to track imbalance from IoT devices, store their data in an adapted environment and process them with advanced analytics. Our solution consists of a Lambda Architecture that collects data from a smart Cane used by elderly people and processes in real-time and batch ways these data to predict imbalance.

keywords : Lambda Architecture, Deep Learning, Imbalance Prediction, Frailty.

I. Sources of Data

The Smart stick is an embedded system based on ESP32 that supports short-range communication (WIFI and BLE) and also supports LoraWAN communication technology through the RFM95 chip.

The smart stick contains a 3D Accelerometer (linear acceleration) and a 3D magnetometer.

We have nine features

- lx,ly,lz for acceleration
- mx,my,mz for magnitude
- raw, pitch and yaw

The output of the Walkane application completes the stick data with a feature for the environment and a binary label for imbalance (0/1). The synchronisation is set up using the BLE connection.

A Smart Stick

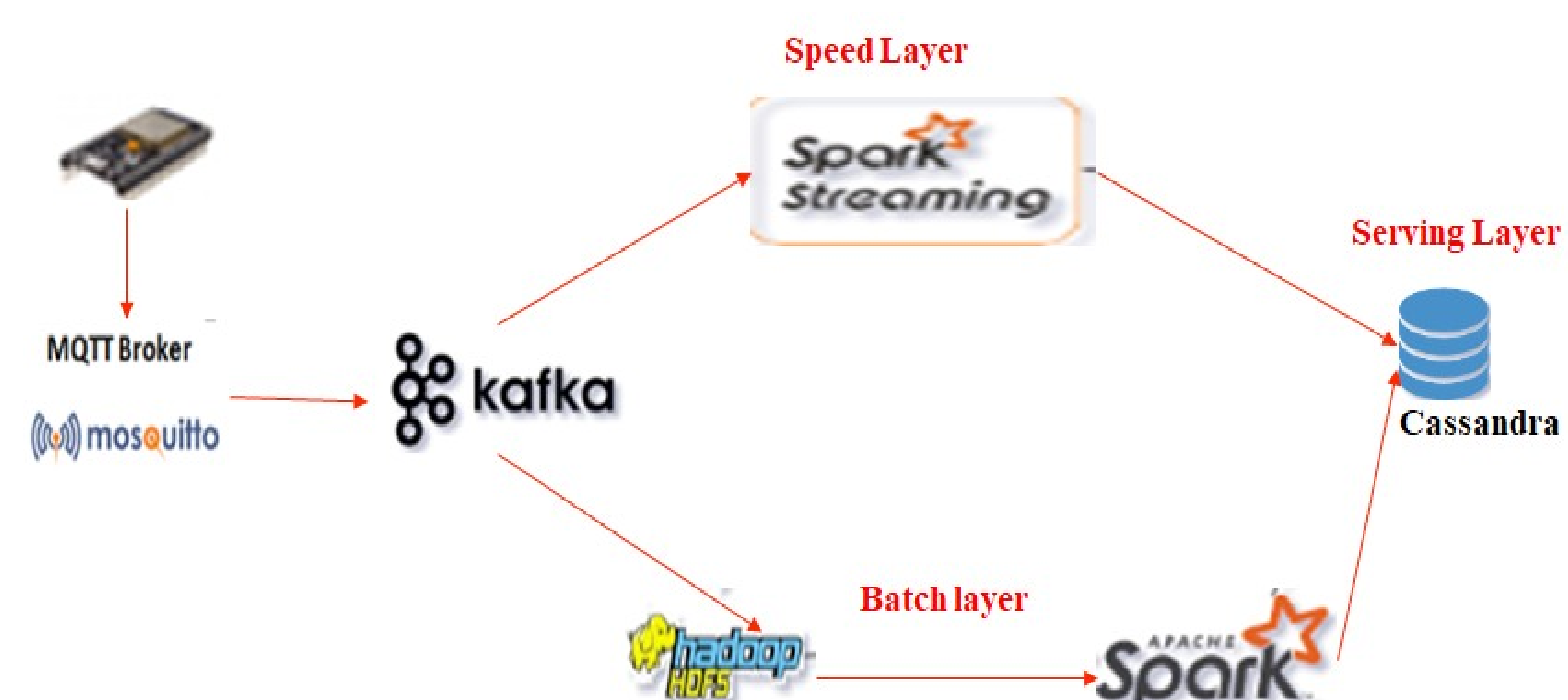


A Labelling Web Application Walkane



II. The Lambda Architecture for Imbalance Prediction

Our architecture is composed of sensor data that are ingested by two layers: (i) **the speed layer** is able to treat in real time the data according to previously defined processes, in our case, we predict for each data if there is imbalance or not with a previously designed model, (ii) **the batch layer** will store data and process them in batch, in our case we fine-tune deep learning models. **The serving layer** is dedicated for data consumption by final users, in our case the doctors can access dashboards of our processed data.



CANE – MQTT Broker

The MQTT Broker 'Mosquitto' receives data from the cane through WiFi links. The chosen approach relies on the cane being a 802.11 STA, and communicating with a server socket on a computer. This server socket then publishes the data on Mosquitto.

MQTT Broker – KAFKA

Once the data is available at the broker, Kafka is in charge of collecting it from the relevant topic and storing it in a temporary storage (Retention disk).

KAFKA – Spark Streaming

Kafka receives the data and injects them into the speed layer for real-time processing represented by Spark Streaming. Spark Streaming performs the format conversion in order to retrieve the measurements from bytes received by Kafka, makes real-time prediction on the data using a prediction model trained in the batch layer and stores the data alongside the predictions in Cassandra and HDFS.

Spark Streaming – HDFS

Spark Streaming uses the Hadoop Storage System HDFS to store the sensor data and the annotation files.

Spark Streaming – Cassandra

Cassandra is a NoSQL database responsible for storing the sensorData.

III. Experimental results

To experiment our approach we develop an Artificial Neural Network. This model was experimented on the dataset collected from the second scenario. The dataset was divided into 1710 records for training and 840 records for test (70%,30%). Despite the small amount of data, the achieved accuracy on test set exceeds 94% while the test loss is evaluated to be almost 0.18. Our results are encouraging, they confirm the potential of deep learning techniques in predicting imbalance based on motion data.

Scenarios	Hurdles	Events	Venue
Scenario1	-Stairs -2 doors	-Normal walking - Go down-stairs - Go up-stairs	Hall upstairs
Scenario2	-Stairs -2 doors	-Normal walking - Go down-stairs - Go up-stairs - 2 imbalances	Hall upstairs
Scenario3	-Slope -2 doors	-Normal walking - Go down the slope - Go up the slope	Connected Health Laboratory

Experimental Settings

IV. Conclusion and Perspectives

This work presents a big data architecture in the form of a data tunnel which aims to detect a possible imbalance in the person motion and therefore to inform the geriatrician or the doctor of a possible frailty state. For perspective, we aim to complete the interconnection between Spark and Spark Streaming in order to perform real-time predictions.

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