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# EMOMETRIC: An IOT Integrated Big Data Analytic System for Real Time Retail Customer's Emotion Tracking and Analysis

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**Abstract**

Business Intelligence is an important aspect of any organized commerce. With the growing competition and global outlook of the businesses, metric driven business insight has become extremely important for the corporations to analyse, understand and plan their business in better ways. Understanding customer's behaviour and their sentiments has been an active area of research over a long time. However, due to practical challenges associated with such adaptations, there hasn't been significant work towards customer behaviour and sentiment tracking in physical retail stores. In this work, we have addressed this significant challenge of the retail sector and proposed EMOMETRIC, which is an intelligent trolley that can track customer's emotion and provide a customer behavioural insight through IoT integrated data intelligence running on Apache Spark Cluster. The proposed system uses model based face and emotion tracking under real use case conditions. Results shows that the proposed technique has an overall accuracy of 95% in comparison to the current state of art. The proposed technique also adapts QoS enabled secure MQTT protocol to collect the data by the big data No-sql storage system. It is also observed that the proposed technique is not only fast and accurate but also illumination and pose invariant. This work can be used as a framework to offer emotion as a service through SAAS platform.

**Keyword:** Business Intelligence, Customer Behaviour, Emotion, Apache Spark, MQTT Protocol, No-sql, Big Data.

## INTRODUCTION

Retail is one of the leading industries, which is drawing significant innovation in different business aspects for improving sales, reduction in operational cost, better customer relationship, better services, retaining customers, predicting trends and so on. Traditionally, for retail businesses success has been dependent on the business skills and service quality of the human resource. However, with the advancement of technology more and more businesses are looking to integrate technology to various aspects of business in order to enhance the profitability as well as scalability of the business. Gaku and Takakuwa [1] showed how a simulation driven model for data analytics can help understanding the business process. They also demonstrated the basics of predicting future trends depending upon predictive analytics with big data[2].

Carson et al. [3] argue that big data analytics is nothing but a data mining task on a huge unconstrained patterns. Generally, in a data mining task an objective or result is known before hand, and is searched or extrapolated from the available data. Data Analytics on the other hand is a data science to generate unknown insight from the data. Big data is essentially a large volume of data with variety, varsity and velocity. Due to huge number of raw records they preserve, trends and insights which can be extracted from the record using different mathematical, statistical and information analysis system, commonly known as big data analytics.

Ahmed et al.[4] proposed big data analytics using agent based techniques. They have discussed the challenges of big data which includes data representation, redundancy reduction, data life cycle management, analytical mechanism, data confidentiality, expandability and cooperation has to be the biggest challenges in big data analytics. An agent based system is proposed which exhibits artificial intelligence, machine learning and autonomous decision making to deal with such data. The three aspects of data processing by these agents are identified as spatial distribution, heterogeneity and real time processing. Big data analytics should lead to better business decisions. Smarter, faster, impactful decisions collaboratively create an intelligent and smart business decision framework. There are several business areas which can draw an independent analytics. Some of them are

- Customer interaction
- Order management
- Event management
- Performance monitoring
- Credit risk analysis
- Sales and trading
- Risk management
- Marketing
- Claim services
- Inventory management
- Supply chain
- Payment gateways and so on.

E-commerce, M-commerce and physical retail stores are important end-business entities along with customers which forms either B2B or B2C process.

The main difference of big data analytics with data mining is that data mining is more of a reverse engineering where the goal is known and the process is discovered. On the other hand, big data analytics has standard set of processes that can lead to important insights. Supakkul et al. [5] argues that goal oriented analysis is a much better approach than raw data analytics in businesses. They propose GOMA – a goal oriented big data analytics framework that integrates specific tasks of data mining into the big data analytics realm. For example, increase in profitability or decrease in warehouse stock can be considered as business goals. GOMA based approach leads to such data analytics which provides insight about the afore mentioned goals.

Jia et al. [6] explored a unique dynamic pricing system based on stochastic process using electricity retail sector for the case study. Their method proposes establishing a linear mapping between near random customer demand with the pricing using a stochastic process using piecewise linear stochastic approximation. Such a solution essentially is an optimization problem solved by incorporating a set of fixed and random variables. For example, outside temperature, hour of the day, past usage by the customer and so on. Such dynamic pricing is now being observed across wide range of industries like air ticketing, celebrity shows and so on. Therefore, one of the areas of big data analytics is pricing management with collaborated demand and supply analysis.

Often, when we go to a small grocery shop at the next door, the shop owner asks us about our further requirement with probable suggestions like "Do you want milk?". There are personalized recommendations which the shop owner develops through the knowledge of customer and his past purchases. Such recommendations make shopping a seamless and enjoying experience as the customer may not always remember instantaneously what are the other requirements that he needs to buy. Recommendations of diapers when a parent buys olive oil or recommendation of a trouser during the purchase of a T-shirt not only increases the sale but also helps on improving the shopping experience of the customer. Therefore, good recommendation systems are one of the most important areas of big data analytics in retail which are predominantly being used in M-commerce and E-commerce applications. Ali et al.[7] proposed a bio inspired termite colony optimization to build a recommendation system based on adjusting the path in a connected graph of products bought by the customer in the past. They carried out a case study on big bazaar, a large retail chain in India. Burhanuddin et al.[8] proposed a content based recommendation system that employs a pair wise approach for ranking the recommendations where each of the recommendation is generated by pair wise rank of a user and a specific item. They propose a loss function and a similarity function on each pair and generated the recommendation based on a standard iterative optimization process. Gopalachari and Sammulal [9] proposed a web based recommendation system that is dependent on user current session, users past behaviour extracted from the cache and behavior of the other users collaborated in a domain ontology based system. Ontology driven recommendation systems are popular even amongst the online e-commerce and retail system which utilizes users search and purchase history for the recommendation.

Irrespective of the type of analytics and processes, success of any business ultimately boils down to understanding the customer, their needs and efficiently offering services and solutions for the same. Understanding customer preferences, their demand, complaints, expectations can help a business to improve significantly. Therefore, a huge amount of research has been observed in the area of customer behaviour analysis. Customer behaviour analysis in the e-commerce retail is done by utilizing customers search behaviour and click stream data[10]. The data set included timestamp, the time spent on an item, search category, cart overview, order of selecting items, number of click to recommendation, number of exits without purchase and so on. This data is then incorporated into a decision tree system to predict the behaviour of the customer. The work demonstrates the use and adaptation of machine learning with artificial intelligence into analysing and predicting customer behaviour with past trends.

Norouzi and Alizadeh [11] used customer behaviour analysis to predict most likely items a customer is likely to purchase and rank them accordingly for presenting it to the customer. They used a multinominal model with hidden Markov model to rank the products for display. Their method models product purchase behaviour of a customer as a Markov chain with discrete random variables being the data set attributes. Han [12] uses the customer behaviour analysis to segment the customers likely to purchase[11], where their behavioural pattern were analysed to rank the products. A customer segmentation based on purchase and consumption behaviour viz., likely buyers, future buyers, VIP buyers and so on, can significantly help the businesses to focus on prospective buyers. This method used back propagation neural network to classify the customers into pre-existing categories. This is an example of goal oriented data analytics.

Ahmed et al.[13] summarizes various classification techniques and their significance in customer behaviour analysis and ranking. Most commonly used efficient classifiers are Bayes net, naïve Bayes, K-Star, clustering, filtered classifier, END (meta classifier), JReep, RIDOR, decision table, J48, simple cart and so on. They also analysed the effect of social posts among the products by a customer for his behavioural analysis.

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## PROBLEM DEFINITION

Customer behaviour analysis on e-commerce and M-commerce platform is significantly easier than doing the same for retail stores. This is because in the web and mobile based purchases, different matrices like search, click, time spent can be quantitatively recorded for a qualitative analysis. But the same analysis for physical retail stores is extremely difficult because no data corresponding to customer's behaviour analysis is available. Therefore, customer behaviour analysis in physical retail stores is not only a major computational challenge but also a huge business problem. A mathematical qualitative representation of the customer behaviour in physical stores can significantly help in improving sales, customer relationship, shop interior design and overall business development. This work focusses on addressing this challenge and offer a feasible, cost effective and efficient solution for customer behaviour analysis in physical retail store by integrating with machine learning. The overview of the past works and the current state of art in this direction is presented in Appendix – A.

## PROPOSED SYSTEM AND METHODOLOGY

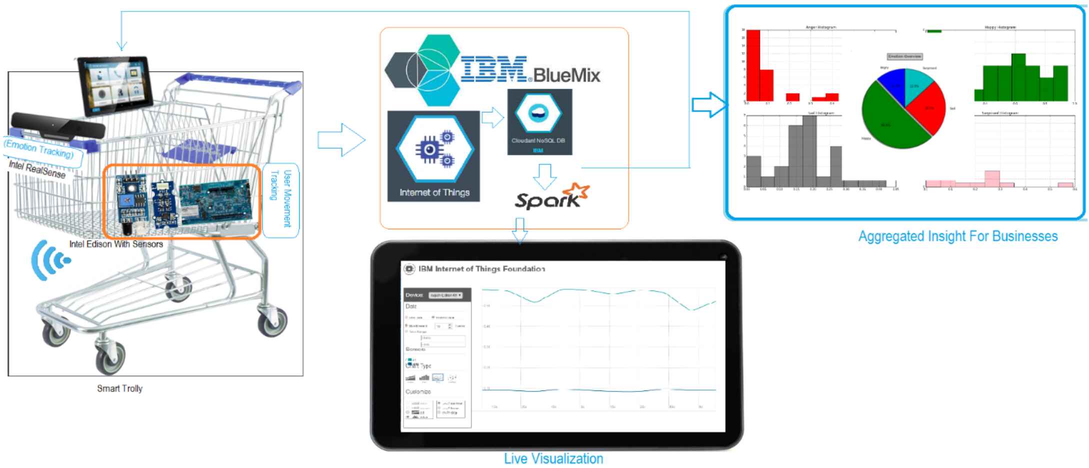



**Figure 1.** Overall Architecture


**Figure 2.** Technical Overview of the proposed system.

In this work, we have proposed a novel solution for analyzing customer emotion and obtaining meaningful insight for the retail businesses by integrating machine learning, computer vision and data science techniques as depicted by Figure 1 and 2. Our contribution of work is in achieving a very high frame rate, fast and real time face detection system using node.js. Our model based face detection system achieves a frame rate of 23fps which is about 10 frame per second higher than frame rate associated with Adaboost based technique which is been commonly used[21]. We developed a smart trolley loaded with a camera and a IoT[15] processor. We have used Intel Edison Kit for interfacing the camera. The frames acquired from the camera is sent to a local server using MJPG. The local server receives MJPG stream from all the smart trolleys enabled with our system. The local server then runs a local face detection system by using model based face detection technique. The details of this technique is elaborated in the following section.

Once the face boundary of the customer is tracked, the data along with the trolley id is stored in is stored in No-Sql Mongodb database in IBM Bluemix. Therefore, every data record contains the id of the trolley, the customer emotional data. We also enable the trolley with weight sensor[14]. Therefore, the amount of purchase that the customer does, is mitigated to the server along with customer emotion data. The basic idea is to link customer emotion with his purchasing behavior. It is planned to incorporate RFID or any such smart card based system for the products in order to track the buying behavior in a much comprehensive way. But for this particular proposal we could not enable any smart card system to identify the products. We also enable three axis accelerometer with this smart trolley. The accelerometer tracks the customer's data. Therefore, the trolley id, customer emotion, customer mobility data, the weight on the trolley is obtained and sent to the database.

Because the amount of data being generated with 23 fps tracking rate, 6 trolleys being used in the pilot phase is huge, playing with webserver and database server fails to process such huge amount of data. Hence, it is proposed to use big data system to process this data. Hadoop is one of the most common big data architecture which is being widely used in many enterprise applications. However, recent advancement in the big data technology and comparative study has revealed that apache spark performs magnitude time better than conventional Hadoop based system with special clustering and parallel computational ability. The apache spark cluster can outperform Hadoop cluster in processing and data analytics. Therefore, the gathered data is processed by apache spark system in the background.

'R' and Python are two most popular programming languages for data science and big data analytics. Apache spark is written in R language. Therefore, many of the enterprises prefers 'R' language for data analytics of any data processed by apache spark. However, due to less vibrant community in comparison to python and lack of as many numerical and scientific processing libraries that python has, hence python is preferred over R language for the data analytics.

In this work, pandas is used to read the data frame which is acquired as an unstructured remote data from the apache spark cluster. The data acquisition step requires user's authorization which is provided with the access token generated by IBM bluemix at the time of data acquisition. Therefore, the overall data analytics is implemented over extremely secured data access channel. This ensures high degree of confidentiality and security for extremely privacy critical customer data.

Once the data is phased from apache spark storage cluster into a pandas dataframe, aggregation analysis is carried out for extracting the insight from the data. Hour wise aggregation of the data is performed based on the data of customer's aggregation, data based on user mobility and so on. This aggregated data is then subjected for regression analysis. The regression correlates the weight of the trolley with the customer emotions and gives an extremely meaningful insight of the purchasing behavior depending upon the mood of the customer.

The aggregated report of the emotion data is presented to the retailer so that he can analyze and understand the customer's behavior or purchasing trends.

### *A. Facial Model*

The emotion tracking is performed by fitting a facial model of the customer in a video frame from an approximate initialization. In our case the facial model consists of 70 points, which is shown in figure 3.

**Figure 3.** The Facial Model.

The algorithm fits the trained model by using 70 lightweight classifiers, i.e. one classifier for each point in the model. Given an initial approximate position, the classifiers search a small region (thus the name 'local') around each point for a better fit, and the model is then moved incrementally in the direction giving the best fit, gradually converging on the optimal fit. The fitting process on a grey scale face is shown in figure 4.

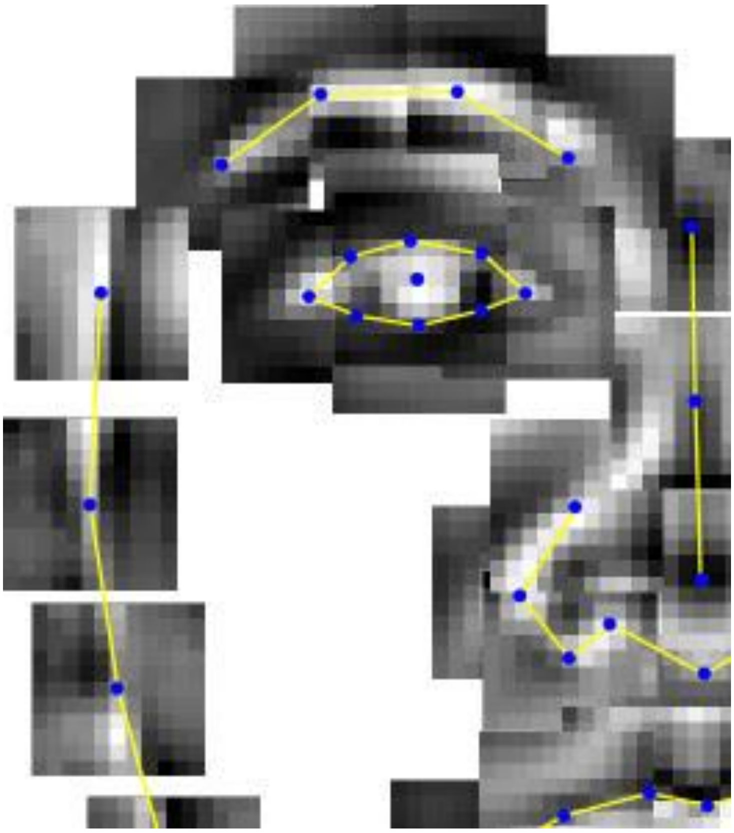


**Fig. 4.** Fitting of model data points on an image.

A facial model is annotated face data. As faces from one person to another doesn't vary much in terms of the geometry, a facial model is easy to construct. Figure 4 shows the model used in this work which is a labelled face dataset to construct a face model.

To build a model from these annotations, we use PCA. The mean points of the annotations are calculated first and then the mean points of all the annotations are found out. PCA is used to extract the variations as a linear vector set. A typical facial annotation extracted by model fitting process is shown in the figure 5.

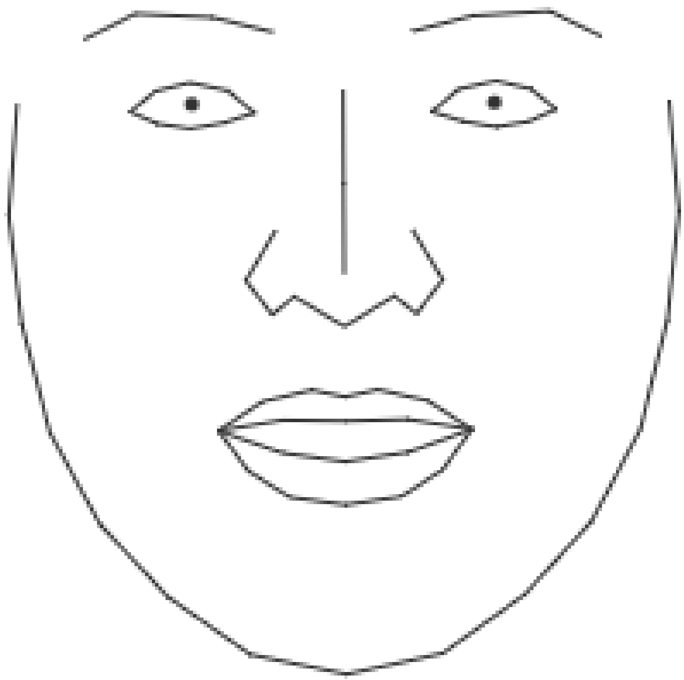


**Fig. 5.** Approximated face annotation.

PCA extracts the set in order of importance. Since the first few elements of the set represents majority of the facial posture variations, rest of the parameters are discarded which does not cause significant loss in model precision. PCA extracts basic variations from posture, such as yaw, pitch, then followed by opening and closing mouth, smile, etc. Any facial pose can then be modelled as the mean points plus weighted combinations of these components, and the weights can be thought of as “parameters” for the facial model. The overall block diagram is shown in figure 6.

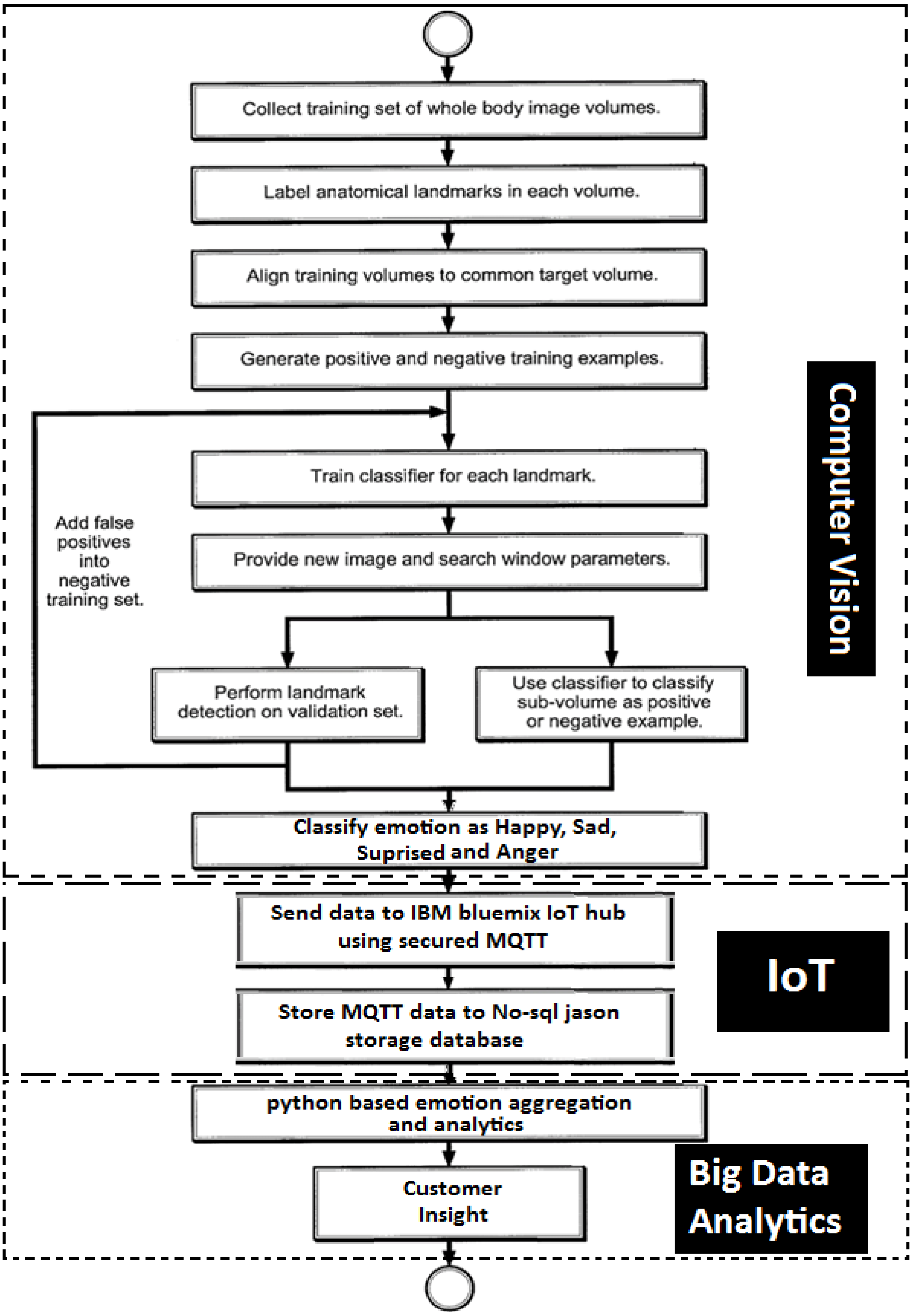



**Fig. 6.** Overall Block diagram of the proposed work.

Constrained local models are used for extracting the facial parameters from the face image. The CLM maximizes the likelihood of the model parameters and is given by

$$p(\mathrm{p} \mid \{l_i = 1\}_{i=1}^{n}, \mathrm{I}) \,\alpha\, p(\mathrm{p}) \prod_{i=1}^{n} p(l_i = 1 \mid x_i, I) \text{ ..... (1) [23]}$$

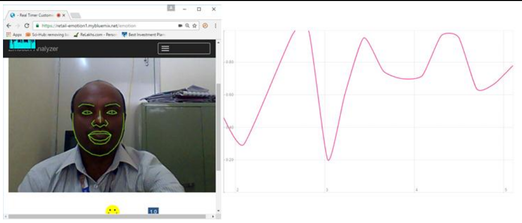
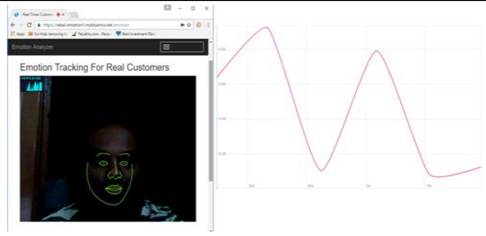
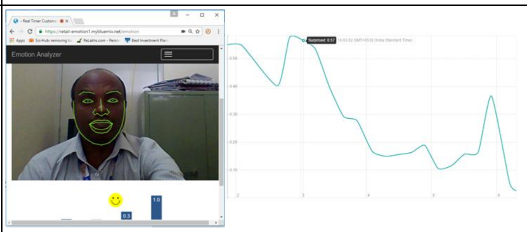
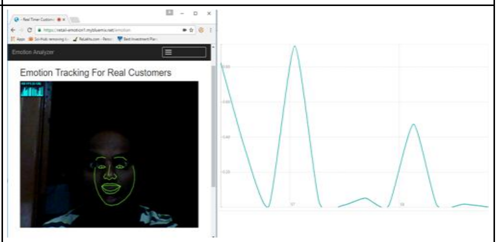
This objective function can be minimized using iterative gauss newton optimization procedure and thus takes the form

$$\Delta p = -H_{GMM}^{-1} \left( \tilde{\Lambda}^{-1} p + \sum_{i=1}^{n} \sum_{k=1}^{K_i} w_{ik} J_i^{T} \sum\nolimits_{ik}^{-1} \Delta x_{ik} \right) \text{ ..... (2) [23]}$$

In this section we have provided the overview of the methodology being used in this work along with model representation. This section also shows how computer vision technique is integrated with IoT and Big Data Analytics are integrated to offer a real time innovative solution for the retail businesses to help them understand their customer in a better way. All the components presented in this section are thoroughly tested some of the current state of art. The testing, experimentation and the findings is presented and discussed in detail in the next section.

## RESULTS

TABLE I CUSTOMER EMOTION AT DIFFERENT INSTANCES OF THE DAY

| Mood | With good illumination | With less illumination |
|---|---|---|
| Happy |  |  |
| Surprised |  |  |

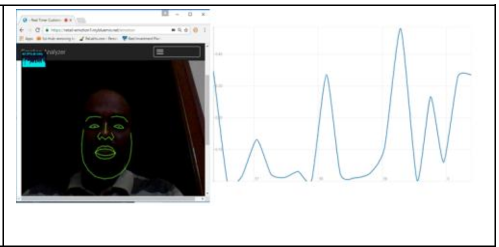
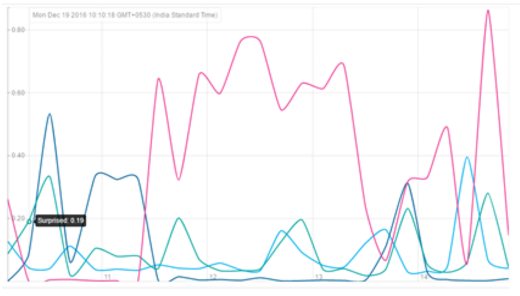
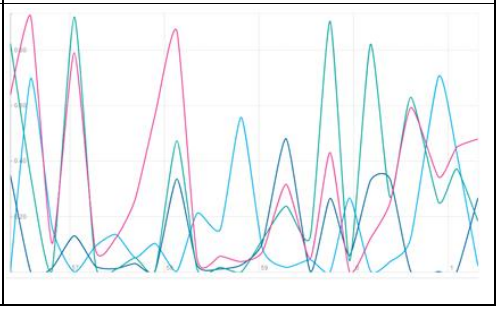
| | | |
|---|---|---|
| Sad |   |  |
| Angry |  |   |
| Combined |  |  |

Table I shows time analysis of customer's emotion at different instance of the day. From the result it can be seen that under different real time scenarios the tracking is perfect. The FPS (Frame per second) data shows a great frame rate of 23 frames per second. This also is a proof that our system is extremely real time. This also shows that our system is independent of light intensity and pose variation. The system can accurately track the pose of the customers at every time of the day and under real use-case conditions. It is also observed that the system produces extremely high throughput while mitigating the data to cloud service provider. The bandwidth management is performed by calculating the average number of active sessions and distributing the Jason format load into each of the sessions where one session represents the tracking for one individual customer.

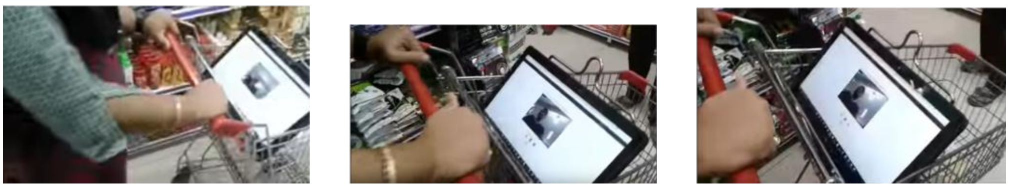


**Fig. 7.** Sequence of Real time tracking session of customer emotion

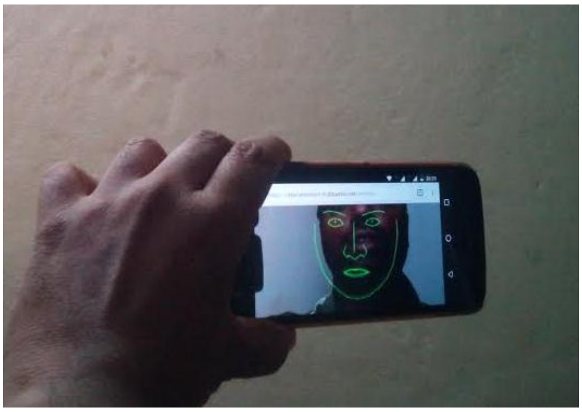


**Fig. 8.** Emotion capture using a low cost mobile

```
root
 |-- _id: string (nullable = true)
 |-- _rev: string (nullable = true)
 |-- deviceId: string (nullable = true)
 |-- deviceType: string (nullable = true)
 |-- eventType: string (nullable = true)
 |-- format: string (nullable = true)
 |-- payload: struct (nullable = true)
 |     |-- Angry: double (nullable = true)
 |     |-- Happy: double (nullable = true)
 |     |-- Sad: double (nullable = true)
 |     |-- Surprised: double (nullable = true)
 |     |-- Time: long (nullable = true)
 |-- topic: string (nullable = true)
```

**Fig. 9 (a)** Meta Data

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **397** | 0.412319 | 0.008297 | 0.082973 | 0.056489 | 2016-09-08 19:44:06.200 | 19 | 2016-09-08 |
| **398** | 0.435818 | 0.005398 | 0.098130 | 0.040031 | 2016-09-08 19:44:08.862 | 19 | 2016-09-08 |
| **399** | 0.294227 | 0.003942 | 0.076998 | 0.015520 | 2016-09-08 19:44:27.428 | 19 | 2016-09-08 |
| **400** | 0.328242 | 0.003775 | 0.079657 | 0.023520 | 2016-09-08 19:44:58.320 | 19 | 2016-09-08 |
| **401** | 0.019157 | 0.091146 | 0.599761 | 0.001605 | 2016-09-08 19:45:40.439 | 19 | 2016-09-08 |
| **402** | 0.290938 | 0.004782 | 0.090503 | 0.009809 | 2016-09-08 19:45:47.752 | 19 | 2016-09-08 |
| **403** | 0.418383 | 0.005648 | 0.071016 | 0.008834 | 2016-09-08 19:45:57.967 | 19 | 2016-09-08 |
| **404** | 0.065789 | 0.027398 | 0.157332 | 0.096091 | 2016-09-08 19:21:09.686 | 19 | 2016-09-08 |
| **405** | 0.410303 | 0.003420 | 0.089267 | 0.021645 | 2016-09-08 19:22:25.956 | 19 | 2016-09-08 |
| **406** | 0.038364 | 0.308535 | 0.238350 | 0.251374 | 2016-08-23 09:36:54.042 | 9 | 2016-08-23 |
| **407** | 0.018172 | 0.391079 | 0.430548 | 0.252674 | 2016-08-23 09:37:15.670 | 9 | 2016-08-23 |
| **408** | 0.044588 | 0.321722 | 0.160710 | 0.099148 | 2016-08-23 09:37:56.534 | 9 | 2016-08-23 |
| **409** | 0.077800 | 0.177293 | 0.084835 | 0.001982 | 2016-08-23 17:34:04.358 | 17 | 2016-08-23 |
| **410** | 0.001059 | 0.950598 | 0.270322 | 0.591457 | 2016-08-23 02:13:25.008 | 2 | 2016-08-23 |
| **411** | 0.388831 | 0.213106 | 0.000940 | 0.035334 | 2016-08-23 02:13:28.890 | 2 | 2016-08-23 |
| **412** | 0.512126 | 0.044876 | 0.017589 | 0.000586 | 2016-08-23 08:31:14.108 | 8 | 2016-08-23 |
| **413** | 0.103992 | 0.071432 | 0.314033 | 0.118234 | 2016-08-23 08:32:03.693 | 8 | 2016-08-23 |
| **414** | 0.125252 | 0.075763 | 0.074410 | 0.183616 | 2016-08-23 08:32:16.879 | 8 | 2016-08-23 |
| **415** | 0.081318 | 0.116807 | 0.028325 | 0.063840 | 2016-08-23 08:34:58.575 | 8 | 2016-08-23 |
| **416** | 0.010334 | 0.281719 | 0.199974 | 0.448355 | 2016-08-23 08:35:15.638 | 8 | 2016-08-23 |
| **417** | 0.017335 | 0.775052 | 0.003845 | 0.057088 | 2016-08-23 08:36:15.601 | 8 | 2016-08-23 |
| **418** | 0.136325 | 0.015767 | 0.270526 | 0.037003 | 2016-08-23 08:20:48.096 | 8 | 2016-08-23 |
| **419** | 0.212806 | 0.008251 | 0.199533 | 0.019189 | 2016-08-23 08:21:06.315 | 8 | 2016-08-23 |
| **420** | 0.136948 | 0.088126 | 0.039350 | 0.029727 | 2016-08-23 08:21:33.773 | 8 | 2016-08-23 |
| **421** | 0.007757 | 0.364961 | 0.105792 | 0.384335 | 2016-08-23 08:21:53.524 | 8 | 2016-08-23 |
| **422** | 0.013485 | 0.164212 | 0.005995 | 0.531925 | 2016-08-23 08:36:30.184 | 8 | 2016-08-23 |
| **423** | 0.091647 | 0.114054 | 0.022624 | 0.024465 | 2016-08-23 08:37:55.575 | 8 | 2016-08-23 |

**Fig. 9 (b)** Sample Collected Data

```
#General Visualization
plt.figure(figsize=(20,10))
plt.plot(ds.Angry)
plt.plot(ds.Happy)
plt.plot(ds.Sad)
plt.plot(ds.Surprised)
plt.legend(['Angry', 'Happy', 'Sad', 'Surprised'], loc='upper left')
plt.title('Raw Emotion data')
plt.show()
```

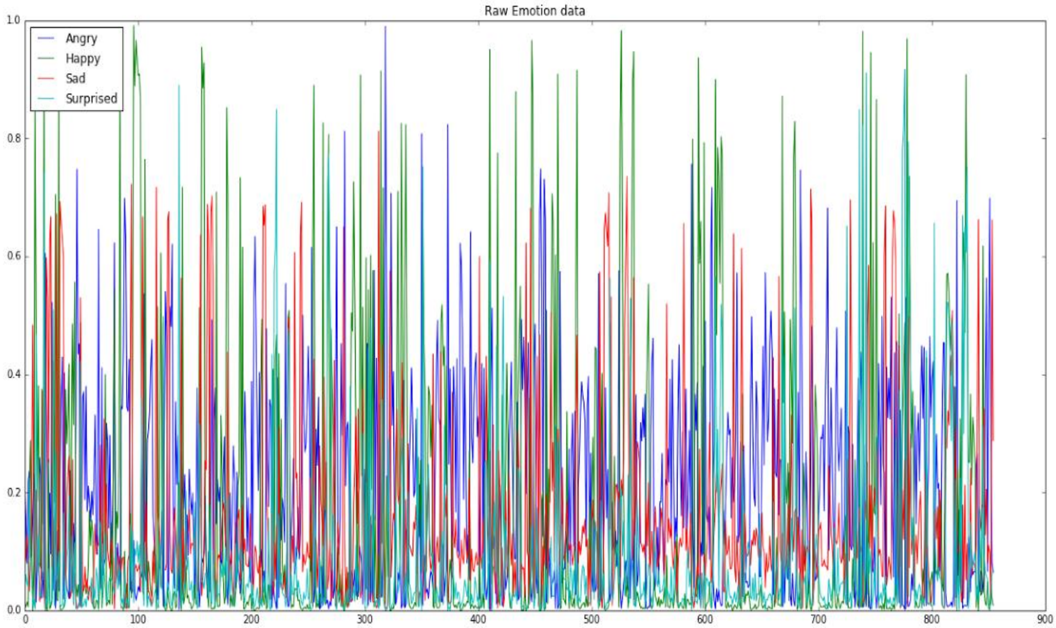



**Figure 10.** Raw emotion data histogram

Combined mood plot of Table 1 shows the tracking multiple emotions simultaneously. Therefore, it can be concluded that the proposed system not only is capable of real time tracking but also multiple simultaneous tracking under real load situations. Because in a real retail scenario, a customer will move his head constantly while the person is looking at various products. The tracking fails to fit the model on the face with accuracy. The loss of tracking is dominant mainly under low light condition. However, even in such condition the tracking regains with compensated frame rate. This clearly shows the efficiency of the proposed technique. Figure 7 shows real time tracking of the customer data in the real retail environment. It can be observed that a female customer being tracked efficiently using the proposed technique. This shows the proposed technique is independent of age and gender of a customer. Figure 8 shows the tracking from a low cost mobile device. It makes it possible for a retail owner to deploy several such trolleys without a need for insignificant investment. Result in table 1 and Figure 8 also proves that the proposed technique is independent of the quality of the camera and the resolution. Hence, a simple Raspberry-pi device connected with a 640 x 480 webcam can also be efficiently used for tracking purpose. The data sample and its corresponding meta data is depicted in figure 9. Figure 10 shows that the raw data does not convey any significant information because of the large volume of data which needs to be properly filtered and analysed. This elaborates the significance of data mining and analytics techniques that are being used here which are presented in the Figure 11.

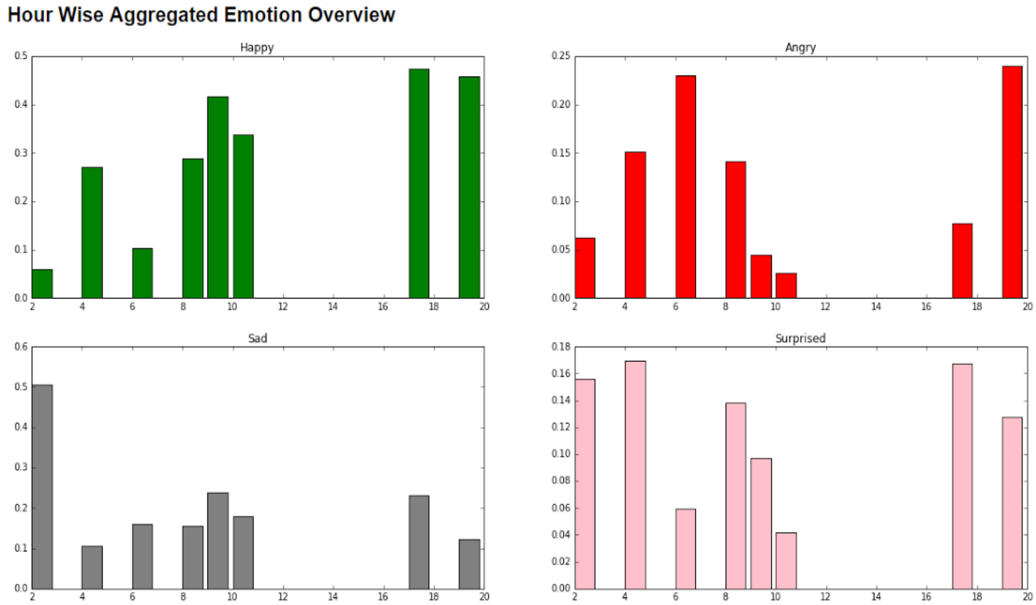



**Fig. 11.** Hour wise aggregated emotion date from a customer.

Figure 11 represents the hour wise aggregation of customer emotion data which is provided as business insight to the retailer. Such insight can be used by the retailer to obtain meaningful business intelligence. This also shows that the proposed system can be effectively used across wide range of customer segments and wide variety of business cases.

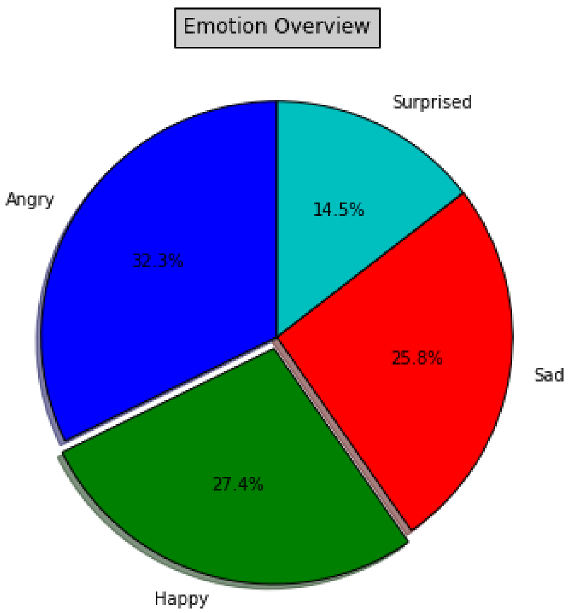
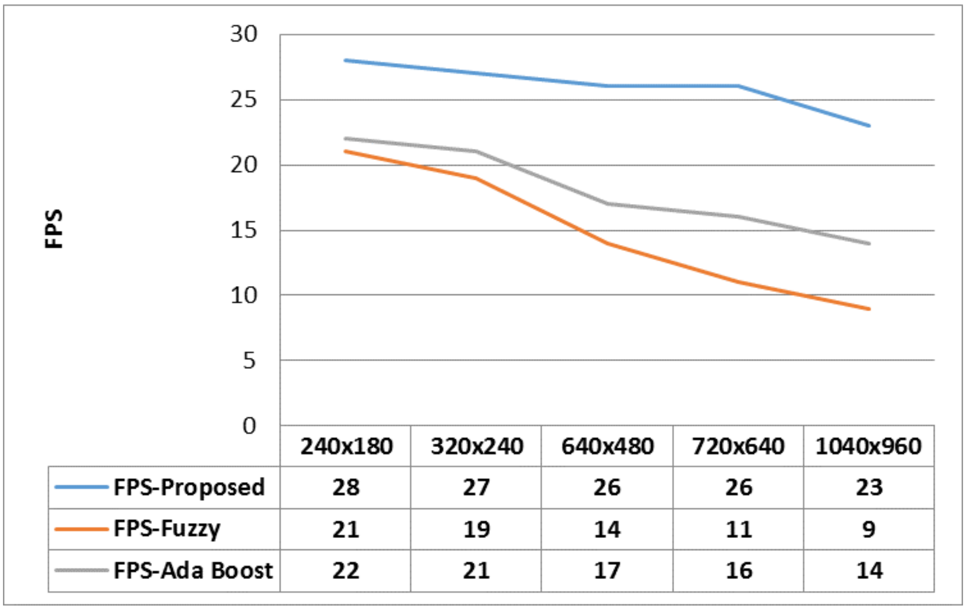



**Fig. 12.** Pie chart plot of emotion data of the customers.

Figure 12 shows the pie chart index of the customer data. This provides an overall insight about the overall emotion classification of the customer in a real world context which helps the businesses to work on the aspects of businesses which leads to poor customer response.

### A. *Time complexity Comparison of proposed method with current state of art*

Figure 13 shows comparison of average frame rate between proposed model based emotion classifier with Adaboost based classifier and fuzzy based emotion classifier. Both fuzzy and Adaboost methods are implemented in opencv where mjpg stream is captured and given to precompiled c++ based opencv component through ssmpeg (open source cross platform video, audio, image encoder).



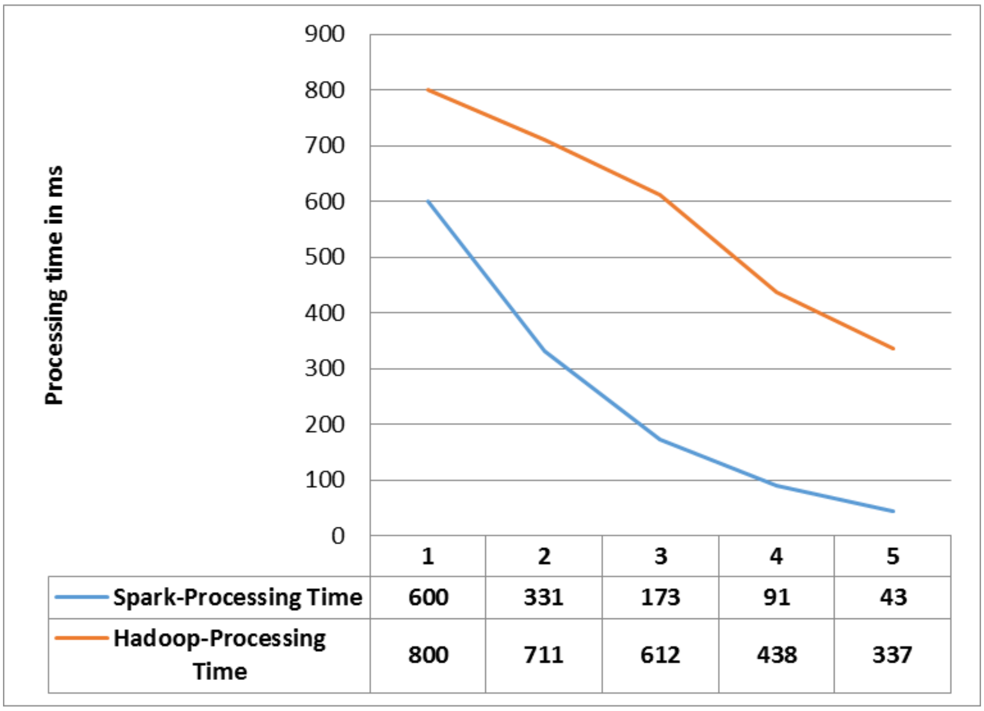

| | 240x180 | 320x240 | 640x480 | 720x640 | 1040x960 |
|---|---|---|---|---|---|
| FPS-Proposed | 28 | 27 | 26 | 26 | 23 |
| FPS-Fuzzy | 21 | 19 | 14 | 11 | 9 |
| FPS-Ada Boost | 22 | 21 | 17 | 16 | 14 |

**Fig. 13.** Comparison of the proposed technique with Fuzzy and Adaboost classifiers.

The result clearly shows that even with fast c++ pre compiled libariries, both fuzzy as well as Adaboost classifiers produce extremely low frame rate. Even though emotion data lead to bluemix server is about 10 records/sec, low frame rate results in missing key customer components like sudden excitement. The overall effective data rate for the latter is therefore effected and we only obtain an effective record rate of 6-8 records/sec for the other two methods making them less reliable in comparison to proposed technique. Also, we need a separate local server for processing the frames in the other techniques making them dependent on the load and signal quality of the local network. Therefore, our technique is more scalable as the algorithm can be running in the edge devices without the need for a fog computing local environment. For the proposed method we compromise only 7 frames/sec whereas the Adaboost and Fuzzy based techniques compromises almost half and two third of the total frames/sec respectively.

*B. Time complexity analysis of Hadoop and Apache spark cluster for the proposed technique and Time complexity Comparison of apache spark and Hadoop cluster for varying input load*

The earlier experiments show that the proposed technique is much more scalable and reliable in comparison to the other state of art in a retail time customer emotion tracking context. The next objective is to validate the choice of big data system for processing the data.




| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Spark-Processing Time | 600 | 331 | 173 | 91 | 43 |
| Hadoop-Processing Time | 800 | 711 | 612 | 438 | 337 |

**Fig. 14 (a)** Comparison of Processing time with number of nodes.

This experiment is divided into two parts: where we analyze the performance of both Hadoop as well as apache spark cluster by varying the instance nodes in both of them. An instance node is a virtual machine running in a cluster with full cooperative integration to business logic broker. Figure 14 (a) shows instance versus processing time. Figure 14 (a) clearly shows that increase in number of instances results in exponential processing improvement for apache spark based cluster whereas it results in only linear improvement in the case of the traditional Hadoop cluster. The processing time is measured as complete time to aggregate the data and produce figure 10 to figure 12. we adopted python as the analytic program. As apache spark is built on R program, shifting to R based processing will result in further improvement in performance. All these experiments were conducted over a sample of 3000 records and without acquiring new emotion data, to keep the input matrix consistent.

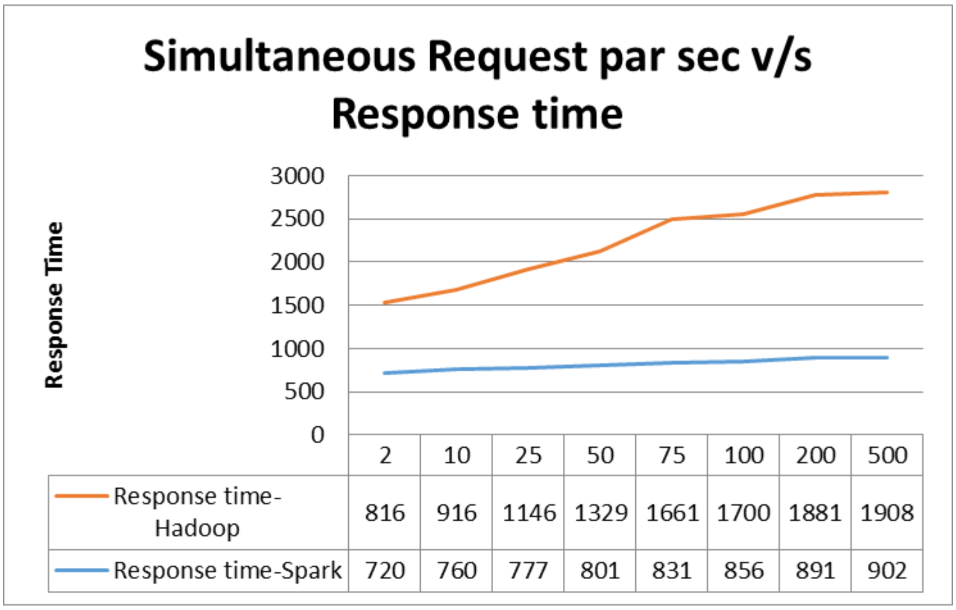



**Fig. 14 (b)** Comparison of Processing time with simultaneous requests per sec.

This experiment was conducted by keeping the number of instance nodes to 4 and generating simultaneous aggregation queries from the end user emulating the retail shop owners. We used automated testing suit built in .net to generate simultaneous queries through multiple browser instances at time interval events. The result clearly shows that apache sparks performance for extremely heavy load is well balanced in comparison to a Hadoop cluster performance (which degrades significantly beyond the moderate load). Therefore, the proposed spark based cluster is more acceptable in real time context for providing our solution as a SaaS based model.

*C. Recognition accuracy comparison*

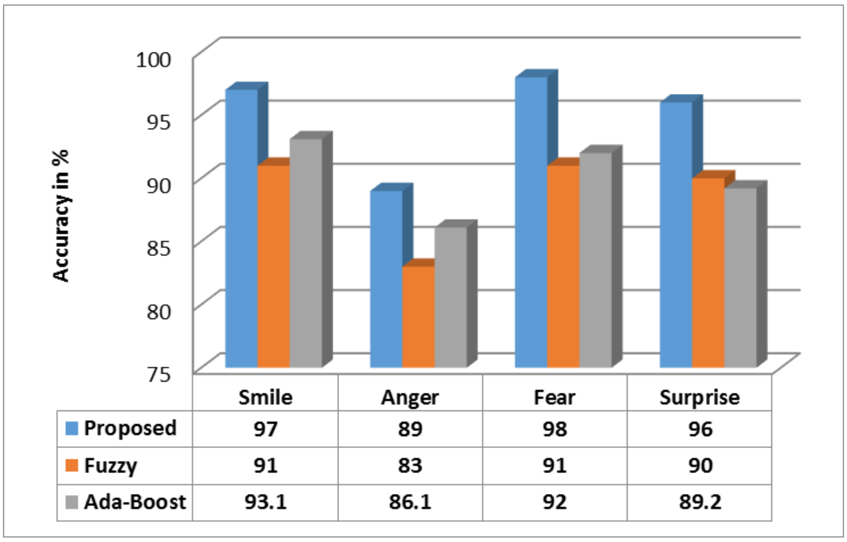



**Fig. 15.** Recognition accuracy for various emotions.

This experiment was conducted by asking the user to keep his facial expression consistent during a session of 30 seconds and then comparing number of correct detections. For example, for a smile test session, the proposed technique should be 23 smile instance detection in a second where an emotion is considered to be dominant if its percentage is greater than or equal to 60%. In case the system detects 21 smile instances in that specific second, the accuracy for that second of the session would be 91.3% the aggregate of entire 30 seconds for a specific user is obtained. Then, the accuracy is aggregated for a set of 50 users which include 31 male and 19 female candidates, all between the age group of 20-22). The experiments were conducted in six sessions spanned over three days, including acceptable illumination session in the morning and low illumination session in the evening. Results shows that aggregated accuracy of proposed system is extremely consistent for both sessions as well as genders whereas the accuracy of the other two techniques suffers under low illumination and is found to be low specifically for male candidates with facial hair.

## CONCLUSION

Recent advancement in connected devices, artificial intelligence, machine vision, machine learning, big data and data science has resulted in exceptional innovations across different industries. Recent boom in the retail sector requires high end intelligence to improve the business through better understanding of customer preferences and their behaviour. Authors have proposed several techniques in the past for customer behaviour tracking in an online retail context. However, the volume of research in the same direction for physical retail shops has been minimal. We have right to address the problem of understanding customer’s behaviour in large retail shop through an intelligent trolley which incorporates low cost, yet efficient facial emotion tracking combined with IoT and Big Data to provide a meaningful customer behaviour insight to the retailers. Results shows that our technique is robust and efficient for practical pose and illumination variant real time scenarios. The fast model based technique improves upon the popular Adaboost and Fuzzy based emotion tracking system in terms of both accuracy as well as time complexity. The backend processing through apache spark cluster improves the analysis time by multi-fold in comparison to more popular Hadoop clusters. Our system offers a business intelligence to retailers but also provides a unique framework that can be used by various other industries like HR, Fashion, Media and so on.

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