Shoe Style&Size detection System

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***Abstract*—This electronic document is a "live" template and already defines the components of your paper [title, text, heads, etc.] in its style sheet. **CRITICAL: Do Not Use Symbols, Special Characters, Footnotes, or Math in Paper Title or Abstract*. (*Abstract*)**

Keywords—CNN, Big Data, , Hadoop, Intelligent Supply Chain.

I. Introduction

In the increasingly competitive fashion retail industry, companies are aiming to continuously improve their value chain activities [1]. Inventory control is crucial in the fashion retail industry, because the lifecycle of fashionable products are typically very short. Accurate sales forecasting therefore plays a vital role in the profitability of companies. Inaccurate forecasting can result in out of stock or overstock situations which in turn have a negative impact on company profitability [2]. The fashion industry usually have a vast supply chain with many actors, from raw materials suppliers, manufacturers, distributors to the retailers, which makes forecasting demand difficult without the necessary information [1], hence purchasing and Inventory strategies can be supported by vast amounts of historic and real time data collected by the business[3].

Big Data Analytics (BDA) techniques provides companies with greater accuracy, insight and clarity on supply chain operations which leads to increased contextual intelligence across the supply chain [3]. Unstructured data like images and video feeds can be used in data mining and statistical analysis due to large amounts of computational capabilities with multiple cores of CPU and the usage of GPU [4]. Convolutional Neural Networks (CNN) have been widely used in classification and estimation problem such as, image captioning objects detection and speech recognition [4], which has proven invaluable to companies in demand forecasting.

Considering the aforementioned, accurate demand forecasting is therefore vital to aid in purchase order/ stock replenishment within the fashion retail industry. This study intends to contribute to the enhancement of demand forecasting by:

1. Make use of video stream to record the shoes of all customers entering a fashion retailer on a daily basis. A camera (*sensor*) will be set up at the entrance of the store, out of walkway of the customers, but at an angle to get clear recording of the side image of the shoes that enters the store.
2. A Machine Learning (ML) model will be developed and trained with still side images of different shoe sizes and shapes. The model will convert the length of the shoe in the image, and convert it to standard UK shoe size which customers in South Africa use to identify their personal shoe size.
3. The ML model will use the video feed to predict the shoe sizes that entered the store over a given (*n*) period of time. The data collected, shoe size, timestamp and frequency will be uploaded into a Hadoop File System (HDFS), along with data provided from the retailer such as actual sales and purchase order data.
4. The data in the HDFS will be used for Business Intelligence (BI) and Analytics. This data can assist the retailer to get an actual customer profile in terms of the size shoes the customers wear that is visiting the specific store. This will aid in demand forecasting when the retailer replenish their shoes stock levels. Visualisation of the data will be through Reports and Dashboards for user friendly interpretation.

The proposed model will be developed as a Proof of Concept (POC) and further enhancements can be added at a later stage.

II. Literature Review

Please see all individual Literature reviews on assigned topic on Lit review folder.

III. Methodology

A. Experimental Setup

The first part of the project setup is to collect the training data for ML model, two group members went to ShoeCity and used their smartphone to collect images of different types of shoes. All the images that were collected then were categorised by its type. The model aims to classify five classes for the project, sneaker, boot, male formal, female

shoe, causal shoe unisex. Two models were developed, and the one has higher accuracy was selected for the project. The models were trained from scratch.

To prepare for the second part of setup, Testing video was collected from the same shoe store by IP camera. Database configuration was done to process the output file generated from the ML model.

B. Model Design and Description

• Granual data from ML model

The output from the ML model are being stored in HDFS. These large datasets are distributed among the Hadoop cluster and saved in an unstructured format. This dataset comprised of date time of detection, shoe style and branch number (to future proof concept when the model are being rolled out at multiple stores).

• Supplementary data

Supplementary datasets from a RDBMS extracted from the retailer transactional database are stored in HDFS. The supplementary dataset are being used for comparison analysis with the granular data from the ML model. The data that was extracted are the distributions the specific store received in the same date range that we collected the video feed. The dataset comprised of, Style description, SKU description, shoe size and number of pairs ordered. This data are in semi-structured format.

• Structured data

The datasets in HDFS are being integrated and structured with Data Analytic Studio (DAS) for easier legibility. New structured datasets and tables are created using a Structured Query Language (SQL). Relationships between datasets are being created by means of adding primary and foreign keys between tables.

• Data Analysis

Data analysis are being done in Apache Spark. Map and Reduce algorithms were applied to sort and count values in datasets. Apache Spark is ideal for in memory iterative processing. Classification and Clustering are also being done on the structured datasets. New data frames

• Reporting

The output in the form of graphs and reports are generated from our granular, semi-structured and structured data. Reports are made up of the date time and shoe style and a count for the retailer to track the shoes that are entering their store.

Figure 1. Report of shoe styles that entered the store in a given date range

• Visualisation

Easily legible graphs are compiled, for the retailer to keep track of the shoes entering the store. The graphs are compiled in Zeppelin Notebook and Jupyter Notebook, and come in the form of bar graphs, line graphs, pie charts and scatterplots.

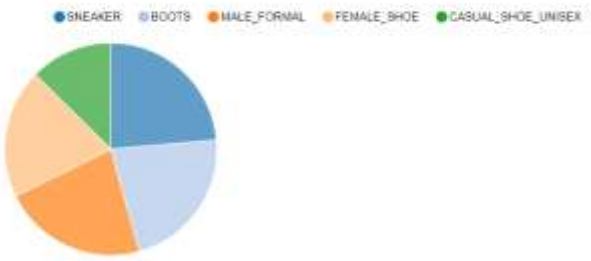

Figure 2. Pie chart of shoe styles that entered the store in a given date range

•

C. Architecture

• Hadoop Distributed File System (HDFS)

HDFS is an open source distributed file system that stores data on multiple machines [10]. HDFS allows businesses to stores large amounts of structured and unstructured data to gain valuable insight. A single node Hadoop cluster was set up to store all the data we collected.

• Hadoop YARN

YARN is a resource management platform to allocate computation resources to cluster and help users manage scheduling jobs for application [10].

• Apache HIVE

HIVE is built on the MapReduce framework. It is a data warehouse that enables users to structure, summarise and run ad-hoc SQL-like queries. The data can be accessed from the HDFS [11].

• Apache Spark2

Spark2 is ideal for in memory data processing. Data scientists commonly use it to implement fast, iterative algorithms. Ideally for clustering and classification of huge datasets [12].

• Apache Zeppilin

Zeppilin is a powerful web-based notebook for data-analysis and visualization [14]. Zeppilin notebook supports multiple languages such as, SQL, Angular, Python, and Spark2 to mention a few.

• Tensorflow

Tensorflow Federated (TFF) is an open source framework for Machine Learning and computations of decentralisied datasets [14]. Tensorflow enables users to use learning algorithms to train their machine learning models.

• Apache Ambari

Apache Ambari is a Hadoop management and administration platform [15]. The platform have developing software pre-installed to manage and monitor Hadoop clusters with an easy-to-use web user interface (UI) [15].

• Relational Databse Management System (RDBMS)

A database that stores data in a structured format, as rows and columns with primary and foreign keys [16]. It relational

because the values in the tables have relationships with each other.

D. Tools and Technology

- The word “data” is plural, not singular.
- The subscript for the permeability of vacuum μ_0, and other common scientific constants, is zero with subscript formatting, not a lowercase letter “o”.
- In American English, commas, semicolons, periods, question and exclamation marks are located within quotation marks only when a complete thought or name is cited, such as a title or full quotation. When quotation marks are used, instead of a bold or italic typeface, to highlight a word or phrase, punctuation should appear outside of the quotation marks. A parenthetical phrase or statement at the end of a sentence is punctuated outside of the closing parenthesis (like this). (A parenthetical sentence is punctuated within the parentheses.)
- A graph within a graph is an “inset”, not an “insert”. The word alternatively is preferred to the word “alternately” (unless you really mean something that alternates).
- Do not use the word “essentially” to mean “approximately” or “effectively”.
- In your paper title, if the words “that uses” can accurately replace the word “using”, capitalize the “u”; if not, keep using lower-cased.
- Be aware of the different meanings of the homophones “affect” and “effect”, “complement” and “compliment”, “discreet” and “discrete”, “principal” and “principle”.
- Do not confuse “imply” and “infer”.
- The prefix “non” is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the “et” in the Latin abbreviation “et al.”.
- The abbreviation “i.e.” means “that is”, and the abbreviation “e.g.” means “for example”.

An excellent style manual for science writers is [7].

IV. Results and Discussion

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper; use the scroll down window on the left of the MS Word Formatting toolbar.

A. Classification Model Results

The classification model for the proposed system was implemented using 2D convolutional neural networks (2D-CNNs) using the TensorFlow Keras API for the implementation of the Keras model layers. Therefore, this section of the paper provides an overview of the performance of the classification model.

Following is a confusion matrix of the training dataset of used on the classification model.

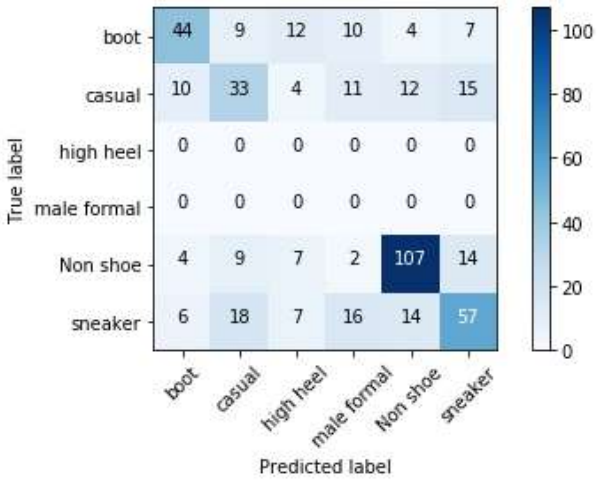

Figure 3: Confusion Matrix for Shoe classification model

We trained the model on a total of six classes of which five of those classes represented actual shoes, and the one class represented a class of non-shoe objects. From the figure above we could notice that the model is not necessarily a ‘best fit’ model for the shoe dataset we trained it on – there was a huge variety of shoe classes but within the different classes there were shoes that had similar shape and texture and this may have caused the confusion or misclassification of some shoes. We noticed that the model better classifies the sneaker type of shoe than the boot and casual shoe. We could also notice that the high heel and male formal shoe were the most misclassified shoes in the dataset. Most of the high heels were classified as boots this is because of the similar shapes of the shoes, and the male formal shoes were often classified as sneakers instead of their true labels. The model produced an overall accuracy of 63.6% for the training dataset which was sufficient to make reasonable predictions.

B. Business Value

Inventory control are crucial for business to profitable [7]. A great amount of operating costs goes into inventory management in businesses. If they order too little they miss out on valuable revenue through sales and if the over stock they extra for storage and movement of stock. Businesses make use of historic Point of Sale (POS) data to forecast demand, along with market trends. This data is vital in getting the right amount and products in their stores [8]. Unfortunately POS data is fairly limiting and probably the biggest negative factor is that it is historic. POS data do not tell the business much about their customers, for example in the shoe retail industry, did the customer buy the shoes for her/ himself, did the customer get what they came for or did they settle for something else? What about the customer that did not make a purchase [7]? The retail company where the research was done have no data on customers that does not make a purchase. These are potential customers, but did not make any purchases when they visited the stores, which can be because they did not find their shoe size or style.

Big Data Analytics (BDA) techniques provides companies with greater accuracy, insight and clarity on supply chain operations which leads to increased contextual intelligence across the supply chain [9]. Unstructured data like images and video feeds can be used in data mining and statistical analysis due to large amounts of computational capabilities with multiple cores of CPU and the usage of GPU [9]. Convolutional Neural Networks (CNN) have been

widely used in classification and estimation problem such as, image captioning objects detection and speech recognition [9], which has proven invaluable to companies in demand forecasting.

A Machine Learning (ML) model developed use the video feed collected (of customer's feet/ shoes) in a fashion retailer store and provide raw data on shoe style and at a later stage will also provide the shoe size. See below extract of the output from the ML model:

```
%spark2.pyspark
df2.select([c for c in df2.columns if c in ['Shoe Type','Time Stamp']]).show()

+-----------+----------------+
|  Shoe Type|      Time Stamp|
+-----------+----------------+
|  Shoe Type|      Time Stamp|
|       boot|2020/07/20 11:13|
|male_formal|2020/07/20 11:30|
|    sneaker|2020/07/20 11:28|
|    sneaker|2020/07/20 11:19|
|male_formal|2020/07/20 10:45|
|male_formal|2020/07/20 11:33|
|     casual|2020/07/20 10:41|
|  high_heel|2020/07/20 10:50|
|    sneaker|2020/07/20 10:37|
```

Figure 4. Granular data from ML model

This raw data was uploaded into Hadoop Distributed File System (HDFS) for storage and structuring. A supplementary dataset from the retailer was extracted from their Relational Database Management System (RDBMS) for comparison analysis. The retailer data below represents a subset of the replenishments the retailer submitted for the same week the video feed was collected.

```
%spark2.pyspark
df.select([c for c in df.columns if c in ['CLASS_DESC','SHOE_SIZE','NO_OF_SHOE_PAIRS']]).show()

+----------+---------+---------------+
|CLASS_DESC|SHOE_SIZE|NO_OF_SHOE_PAIRS|
+----------+---------+---------------+
|CLASS_DESC|SHOE_SIZE|NO_OF_SHOE_PAIRS|
|  LDS BOOTS|        3|              5|
|  LDS BOOTS|        4|              1|
|  LDS BOOTS|        5|              4|
| MENS SMART|        6|              2|
```

Figure 5. Extract from retailer orders

The granular data from the ML model was 'cleaned' and transformed to do analysis on. Using MapReduce and pySpark we did a count of the number of styles. As per below see comparison of actual style shoes that entered the store versus the styles the store ordered for the same time period.

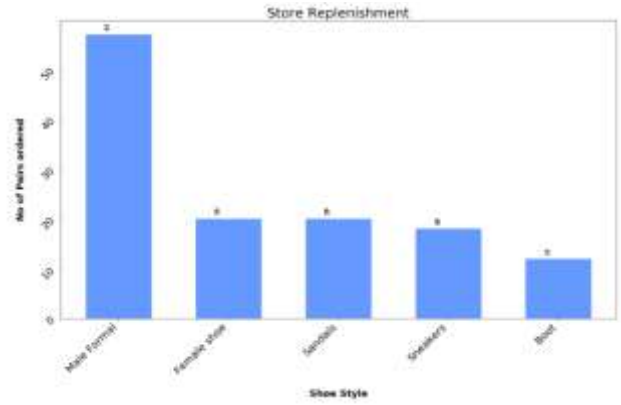

Figure 6. Store replenishments.

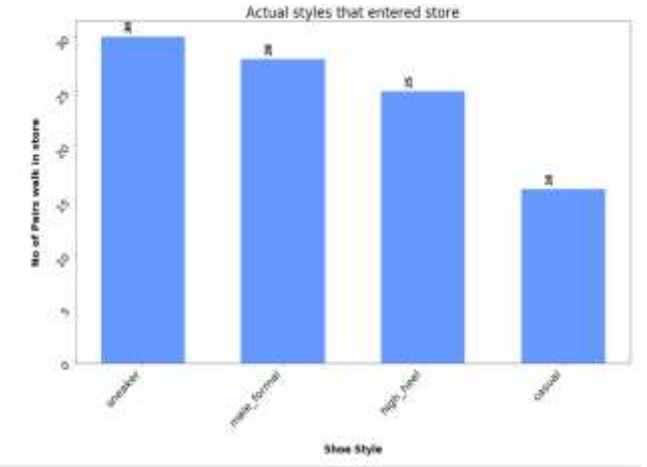

Figure 7. Actual styles entering store.

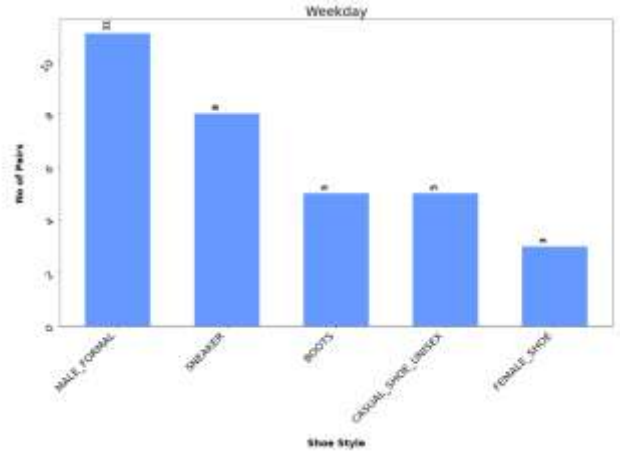

Figure 8. Prominent shoe styles customers wore during the week.

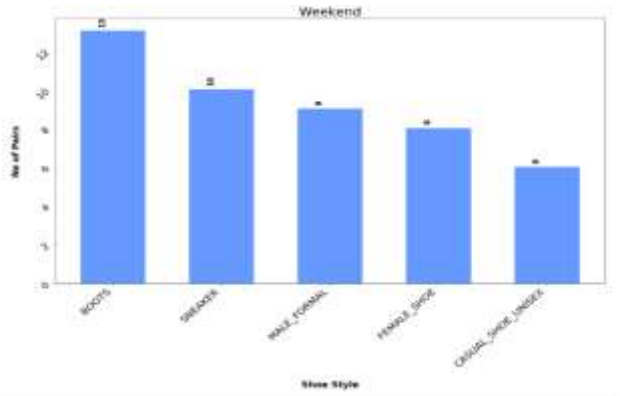

Figure 9. Prominent shoe styles customers wore during the weekend.

With this additional data the retailer have a better customer profile, for example, they know what the prominent shoe styles and sizes their customers prefer are. Also they can see weekend versus weekday shoe styles. This allows them to target their promotions more efficient in terms of *when* to promote certain styles. The date time stamp provided when a shoe is detected by the model can help the retailer ensure certain styles and sizes are available in the store at specific dates in the month, as per customer visiting dates.

If the retailer have a camera in each store to collect data on shoe size and style, the organisation can move from a regional replenishment system to a more detailed store replenishment system. Higher stock accuracy leads to less stock being sold at discounted prices because of unwanted sizes and styles. Retailers can order specific styles and sizes applicable to the store and their customers. Big Data (BD) can indeed improve supply chain (SC) activities. BD can supplement an already efficient SC or enhance an inefficient SC though critical analysis of previously unattainable granular data and turning it into valuable information.

Conclusion and Future Improvements

For future development, we suggest with stronger computational recourses and the model can detect the shoe more accurately and extend the number of shoe classes. To capture the shoe size accurately, instead of using computer vision technique, weight mat can be used as the sensor to capture the shoe print precisely. Facial recognition can also be added to the ML model to predict the gender of the shoe owner, gender classification feature can bring more insight and business value.

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