Leveraging Customer Centered Operations in Retail using Techniques of Artificial Intelligence

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The rapid development of technology particularly Artificial Intelligence and machine learning have brought an impact on our day to day life. Retailers need to go beyond just selling products and need to focus on providing a differential experience. More and more customers are using the internet to search, compare and buy products hence more and more personal data is generated. As customers have a high rate of interaction with retail business and retail business have low-profit margins, they can be regarded as a natural fit business model for the application of AI. This paper discusses the use of AI techniques in the retail industry on building customer relationships and improving customer centred operational efficiencies and customer service. Four areas across the CRM cycle are identified as key areas in which the implementation of AI can be beneficial in retail. These topics are marketing, real-time and historic data analysis, cross-selling and customer retention/churn. Based on the literature review of latest papers published after 2012, the use of AI-based data analysis, predictive modelling, strategy building and data mining approach on the various areas of a retail business is examined. From the analysis of results from the research, survey and experiments examined from the research paper, it was identified that the AI can be implemented in the various areas identified across the CRM cycle and can significantly improve customer service and operational efficiency. Various possible opportunities and current implementation of AI in the retail are identified and discussed in detail.

I. INTRODUCTION

Artificial intelligence techniques have been improving over the years. This research paper is based on how these AI techniques can be used to improve customer centred operations in the retail industry. The paper is based on five main components that affect retail. They are customer retention, customer churn, marketing, cross-selling, and image/video data analytics. All these components are addressed individually in the research papers that were screened. The main goal of our research is to combine each of them and give an overall and combined solution to improve customer operations in retail. Each of these components plays a huge role in the retail industry. The paper discusses what AI techniques can be used to improve each of these components and how to improve them.

Customers are the most important asset in the retail industry. A satisfied customer base can improve sales and increase profit in a company. For that, customer relationships should be properly managed. The key fact is to focus on the right customer segment and the paper will discuss the reasons for focusing on a certain customer segment and how AI technologies such as IoT, Machine learning, data mining, deep learning, manage/video data analytics are used to improve the five selected components.

The paper introduces the use of real-time data analytic techniques (image/video data analysis) that can empower retails to improve their operation and service. Visual market basket analysis (performed through analysing image/video data captured through a camera) is one of those and can significantly improve market basket analysis of customers to predict customer needs. Real-time data analytics also can perform sentiment analysis based on facial expressions of customers and it is helpful to improve customer services. In addition to customer-based analytics, the paper introduces how real-time data analytics can improve shelf out of stock (SOOS) problems. Another important use of real-time data analytics is creating hotspots based on the real-time count of people in-store to understand the flow of customers across the store and to identify high and less crowded areas inside the store to improve customer service targeting that flow.

Customer retention draws attention to how to engage the existing customers to keep buying products from the same firm. It is discussed how customer retention affects a firm and how to improve retention. One area of improvement comes from identifying products which can be promoted with cross selling. Products will be profitable to the retailer in terms of inventory chaining and supply-demand management. Combining the data collected for churn, retention, sentiment, and basket analysis can be used to learn an algorithm to predict the best possible items to market in store and online as well. Additionally, changing operations from the retroactive approach to analyse churn compared to the benefits that predictive modelling and data mining with AI and statistical approaches can bring is examined. Capable of allowing for more dynamic decision making across shorter analysis time frames with the use of historical data. The discussions will be divided by examining AI in non-contractual and contractual churn situations in paid services, E-commerce and brick and mortar stores which are some of the most prominent retail businesses models to benefit. Lastly, understanding opportunities and constraints of implementation of AI in different marketing strategies help a business to make better strategic marketing decisions. Research on the impact of AI in the business where AI is already implemented will help to identify new opportunities and risks that would have been hard to simulate.

II. METHODS

This section will discuss how literature papers and relevant papers were screened. The UNISA library and Google scholar were used to find relevant papers. Some of the keywords are "AI in retail", "IOT in retail", "Customer retention", "Customer churn", "AI in Marketing", "AI in Cross-selling" and "Image and Video Analytics ". All the selected papers were published after 2012 and peer-reviewed with exceptions made on papers with unique topics and original ideas. One paper from 2009 is used which was peer received. It was not from the range but was used because it had better explanations.

Each of these papers was written mostly based on subtopics. And each of them brought some value to the table to build up the selected methodology. The purpose of this paper is to combine all these ideas and give a proper solution on how AI can improve the retail industry. After going through all the explanations and ideas discussed in the papers, each member focused on sub-topics and then the contribution of each subtopic was discussed. After discussing the opportunities and constraint of AI in retail, a methodology was selected.

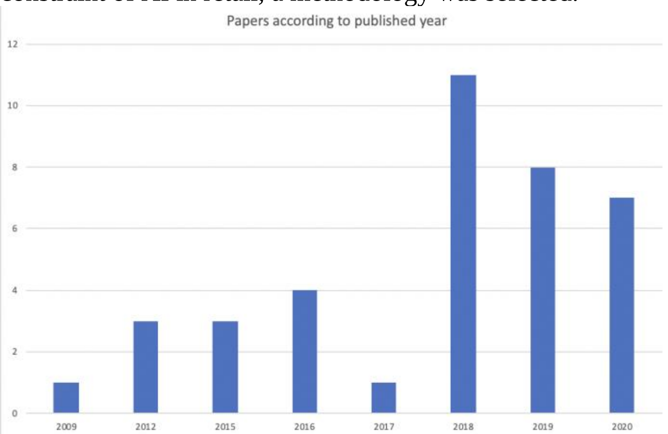

Figure 1: Literature selection by year.

III. LITERATURE REVIEW

A. Customer retention

Customer relationship management plays a huge role in the firm's success. Even though expanding the customer base is important, the most important strategy is to manage the existing customer base skillfully when increasing sales. Then customer retention comes to the spotlight. Customer retention is the process of engaging existing customers to continue buying products in a company. Hence managing customer relationships plays a vital part. According to papers, the retention rate is the measure of customer retention. The retention rate is a significant driver of a firm's profitability. According to the literature papers, customer relationship management can evolve tremendously when CRM turns into AI-CRM (Artificial Intelligent Customer Relationship Management). This will improve the previous traditional customer relationship management techniques with AI-based techniques. There are two main capabilities of AI-CRM [1]. The first one is the ability to leverage big customer data to communicate, understand, and predict customer behaviors. The second one is customer acquisition to improve customer retention. Customer lifetime value measures the importance of the customer to the firm. Customers are given a customer lifetime value according to customer data and they are managed accordingly. This helps to identify the customer segment which needs to be prioritized and manage customer relationships according to the value they have in a firm. The customer data is collected using many different techniques. The purchase history is collected by providing a loyalty card. Every time a customer swipes the card data is recorded. The behavioral patterns are identified using RFID tags and CCTV footage. The CCTV footage is analyzed to find the aisles where customers spend the most time and to find which aisles customers visited during in-store visits [2]. Using these data customer behavioral patterns are analyzed to increase customer retention, and a more personalized experience is given to the customers [3]. According to the literature papers, Machine learning is used in human-like chatbots for communication for dealing with service failure [4]. Also, AI-CRM uses customer behavioral patterns and profile data to predict what ads customers will click on, what products customers will like, or which customers will churn. This predicts unsatisfied customers, and a more personalized customer experience is given to them to increase customer retention to prevent churn [3][5].

B. Churn

Being a subtopic of customer retention, churn supplements knowledge and techniques when implementing retention strategies learning from customers that have already stopped engaging with a business. Previous literature has shown that customer lifetime value (CLV) has been used as a metric to segment customers in non and contractual churn scenarios with logistic regression and Recency, Frequency and Monetary feature models as the baseline [6][7][8]. This section of the report will focus on discussion of more traditional survival analysis and statistical approaches to churn prediction compared to AI techniques (which includes data mining and machine learning). In a publication, the authors found using more sophisticated models with retention strategies based on the boosting technique achieved the highest generated profits, followed by logistic regression, SVM, Pareto/NBD and an RFM model. This is one situation where it is observed that Ai techniques (Boosting and SVM) had continuously outperformed statistical and traditional means of churn detection even when varying experimental parameters. Except on small data sets and when the churn ratio is low [6]. This sets up discussion around when particular techniques should be used, and it was found in a survey of churn literature between 2000-2015. Within the retail banking and telecommunications industry AI has grown in popularity due to their easier use within distributed databases, craze and potentially better performance of ensemble and deep learning [9]. In other industries the literature around churn is not as prominent, however, similarities exist amongst churn prediction methods. As in E-commerce and brick and mortar stores where involuntary churn would be most prominent due to the nature of the business and customer interactions through non-contractual settings. Clustering with k means and logistic regression had found success in each respective scenario [7][10]. However, what the authors focused on was not on choosing the analytic technique but on feature engineering and selection. This process was also stressed on in publications that had performed a survey of churn techniques as the importance of choosing the right variables will greatly impact the accuracy of the model accounting for customer variation over time and selection bias from domain knowledge [9].

C. Cross selling

Intelligent cross selling is a prominent area in the retail industry. It utilizes the inventory data, product supply and customer demand to manage the cross selling of the products to maximize the sales as it is a combination of demand and supply. This can be implemented using two main techniques identified, which are inventory disclosure and inventory chaining. In [11] inventory disclosure was used as the primary method and it provides the opportunity for the retailer to focus on less demanded yet redundant inventory to be promoted as cross products. Content is about a model which discloses inventory levels of firms which sell different types of products. The goal of the research discussed is to avoid unexpected penalties due to lack of sales and unfavorable inventory and to decrease unmet demand for products. In the suggested model the seller is using an information disclosure strategy to meet the unexpected demand fluctuations. As the methodology of the research, factors such as different types of customers, aggregating inventory levels, the commitment of the retailer to disclose the inventory information constantly are considered. With the results of the research, retailers can decide which type of information to disclose to customers to match the supply and demand by cross-selling products. Learning can be used to map with other readings under the same subtopic to propose a research component with AI as in aggregating huge chunks of inventory data, supply-demand fluctuations to assist in boosting the sales from cross selling. In [12] the polynomial algorithm has been developed considering the demand and supply of major items surrounded by minor items. Content of the paper is about an enhancement to prior research done by Zhang et al. (2012) in [13], which is a joint replenishment problem (JRP) model related to demand caused by cross selling. The research published in the paper has reinvestigated the problem suggests a mathematical algorithm to address the problem to obtain global optima. The suggested model and the algorithm consider a multi inventory system consisting of one major item and other minor items. The demand for the major item is independent and demand for minor items are dependent on the demand of the major item. The paper suggests an exact algorithm to tackle the demand fluctuations of minor items with respect to a major item. The computational results of the research reflect that the proposed polynomial algorithm is highly efficient for large-scale problems. This reading can be useful in developing the research component related to cross selling and to propose a model considering the customer demand, product supply and inventory management. From the mathematical exposure gained via the reading, the research content can be enriched using a mathematical approach.

D. Retail marketing

As customers are becoming more and more connected to the retail business online, marketing has not only become an important but essential part of a business. This change in customers behaviour has led many businesses to seek and find new ways to reach and retain customers [14]. More than ever, a retailer needs to understand the market and its customers to implement adaptable and more disciplined management of its marketing strategy. The paper "adoption of machine learning analytical tools in marketing" extensively discussed the importance of evaluation of the implementation of the marketing strategies and the adverse effect on the business due to lack of the evaluation process [15]. The authors further discussed the current implementation of AI and machine learning for data analysis and evaluation of marketing strategies. The paper had clear details on various benefits of machine learning in marketing including clear data visualization, targeting marketing campaigns, detailed overview of customers and focus on indicators of business success. There are various machine learning algorithms and analytical tools available for data analysis. The business needs to understand their data and choose the right analytical tools that suit their needs. The paper by Frisk, Bannister and Lindgren discussed the need for advanced analytical tools for developing the best marketing strategy [16]. This shift from traditional. Studies carried out on various marketing strategies by [14][15][17][18] had discussed the importance and techniques for data analysis in different marketing strategies. The paper on customer journey mapping had discussed various techniques of mining customers' data using the data produced by transaction, interaction and observation of business processes and customer interaction that can be useful to reach and retain customers [19]. The paper compared the success and practicability of machine learning in multiple marketing strategies to improve marketing strategy. Communication and relationship with customers is also an important part of effective marketing. The paper by Bock, wolter and Ferrel had provided examples for strategies to effectively use the customer's data to implement relationship marketing that involves activities to establish, develop and maintain effective relationships with the customers [20]. The paper discussed the use of AI to analyse loyalty card information to help retailers customize their product for each store. Loyalty card that allows the linkage between different retail stores enables the retailers for cross-marketing.

E. Real time data analytics

Visual data(image/videos) is a good source for retail to understand customers behaviour and buying patterns. It can also be useful for many in-store operations. And it is only possible when those data will be analysed using AI. In one literature authors described visual market basket analysis (VMBA) based on the streaming of images received from cameras attached to shopping carts. This paper explained how shopping videos can be transformed (using machine learning algorithms by analysing videos) into customers' behaviours [21]. In two literature authors described how to Improve On-Shelf availability [22][23]. Mobile robot was used that monitors store shelves based on the heatmap of the store to identify Shelf Out of Stock (SOOS) using Deep Convolutional Neural Networks (DCNNs) [22]. In another literature, authors used a different approach for identifying Shelf Out of Stock (SOOS) through a surveillance camera and Convolutional Neural Network. The basic concept of this approach is to identify the change on the shelf by analysing an image that indicates an increasing/decreasing quantity of product [23]. Real-time people counting inside the retail store and visualizing hot spots based on that count is a challenging task. But it is possible using a deep learning method (Convolutional Neural Network regression model) [24]. Relevant algorithms (deep learning) techniques were proposed to identify consumers' demography, behaviour, and satisfaction [25][26]. All the pieces of literature had a similarity in terms of achieving the goal using image and video data analysis powered by Artificial intelligence. However, the purposes and the way of experiment and explanations were different among the papers.

IV. FINDINGS

This section combines the findings that were found from literature and suggestions under each sub section.

A. *Customer retention*

According to a literature review, it is clear that customer retention plays a vital role in the retail industry. To improve retention historical and real-time data are used. Richer the data, the effectiveness of customer relationship management is more effective. After analysing the data if the retention rate is low, the firm may have to focus on proper customer relationship management.

To improve customer retention, it is vital to have better customer relationships. But for a company with a large customer base, it is not an easy task to consider each customer. Even the company that can do that is not worth doing so. The most valuable customers should be identified first to improve customer retention. Selecting this segment from the customer base is very important. It is not the customers who visit the store often or spend more on a single purchase. A customer who visits the store often may be purchasing fewer products every day, a customer who spends more on purchase might be not visiting the store often enough. To select the priority customers, the customer purchase history and behavioural patterns are analysed using AI technologies. Then properly prioritized customer segment (VIP customers) is collected. Then the company can focus more on these customers to drive their sales further. omnichannel businesses face difficulties when managing their customer relationship because the customer also has an online presence. So, it is important to manage both instore and online customer relationships. Even chatbots are used to communicate with customers, language barriers can get in the way sometimes. Using multilingual chatbots can solve this problem. Furthermore, integrating voice-activated digital assistance with these chatbots can expand the customer experience to the next level. These chatbots have more problem-solving ability than a human online chat where an employee has to be online. Because they are trained with neural networks the communication skills can be as good as a human. The model should be trained with a rich test dataset with multiple types of data to reduce prediction failure. In omnichannel retail stores, the customer must get the best experience in both instore and online shopping. Giving personalized (Loyalty) offers and giving a customized online shopping experience using profile data also can improve customer retention.

B. *Churn*

In the literature review, it is observed that the discussion around churn prediction within the retail banking and telecommunications industry is the most prominent and that while there is still much debate between whether AI or no AI-based techniques are better for a specific scenario. What the authors can all agree on is proper considerations on what features to use. Thus, this methodology aims to further investigate how churn is predicted in other industries and to better understand how the data and practices may differ. This should improve understanding of how churn is integrated into a business given the needs and practices of the application. Helping to shine the light on how business and customers may benefit from the use of AI for churn and creates a potential lead into the discussion around areas of future research.

When discussing churn analysis there are often two metrics that are considered, customer and revenue churn; these measures respectively describe the number of customers and revenue lost over a period. Traditional methods for evaluation include cohort reports and grouping customer bases together based on particular attributes such as age, RFM and behaviour. This results in analysis often based around examining graphs and deciding on the best feature/s for grouping in order to calculate churn rates and discover customer groups to focus on. Another approach proposed in this paper comes from predictive modelling and data mining which ranges from a choice of statistical and AI-based techniques. While there is little difference between how different types of churn are detected, not all churn can be feasibly managed and so they are often not considered [9]. This paper discusses the two major types of churn (contractual and non-contractual) which are and pertains to the context of customers that have stopped involving with a business. In contractual churn scenarios, customers enter into a contractual agreement with a business which may exist in the form of subscriptions, licensed software, or service (such as bank or telephone provider). As such, churn may be easily detected through voluntary notice. Non-contractual churn on the other is harder to detect and is often the main type of churn within E-commerce and brick and mortar stores as the tracking of customers are harder. Thus, businesses rely on RFM variables and metrics such as purchase history and lifetime value to segment churned customers below desired thresholds. From this context, the use of predictive methods to predict churn becomes the same when predicting both types as it would largely be beneficial to discover potential customers to churn based on those that have already churned or have low CLV. Statistical methods do this by assuming that the churn can be described by a known probability distribution (which could be parametric, semi-parametric or non-parametric) given other covariates that are used in modelling. While AI techniques discover rules/patterns using the covariates and automatically predict churn customers through self-learning. Some of the most popular techniques include Artificial Neural Networks (ANN), Support Vector Machines (SVMs), decision trees, K-means and ensemble methods.

C. *Cross selling*

As discussed under literature review it was found that cross selling and inventory management has played a major role in setting up the inventory plan aligned with the supply and demand of the products. More insights into customer buying patterns will allow the retailer to perform this in a more efficient manner.

Inventory disclosing and chaining

Inventory returns and unmet demands have been a huge issue in the retail industry resulting in wastage and returning to the supplier [12]. With cross-selling this issue can be mitigated in terms of balancing the demand-supply fluctuations and inventory management. This can be implemented using two main techniques identified via existing research work, which are inventory disclosure and inventory chaining. Inventory disclosing will manage the inventory to be displayed to the customer while inventory chaining will secure the flow of products from the supplier to the retailer constantly.

Supply demand model

In addition to those identified techniques, the selected methodology will suggest how to identify the factors as in research on “Polynomial algorithm of inventory model” such as product supply, customer demand and inventory levels, consumer buying habits to build an intelligent algorithm via machine learning of historic data and real time data to enhance cross selling [12]. Historical data will be collected via analysing customer buying patterns, loyalty history as described in [27][28] and selection of items in the shopping basket from sales records while real time data will be collected via video footage and surveillance cameras [29].

Major and minor product clusters

The technologies that will be used in the suggested method are machine learning and association rule mining [29]. The latter technology is vital in terms of identifying the rules of the shopping basket to identify the major items which are commonly purchased surrounded by minor items which comes as a habit from the customer buying intuition as in [12]. The scale of the sales is important at this point since variety and number of sales would support decision making of product rule formation. Having a large number of sales per week/month will be beneficial for this approach. Following (figure 2) is a high-level diagram of the process flow of cross selling models in the solution. It starts with inventory data, supply demand data fed midway and ends with required predicted products considering the factors explained above.

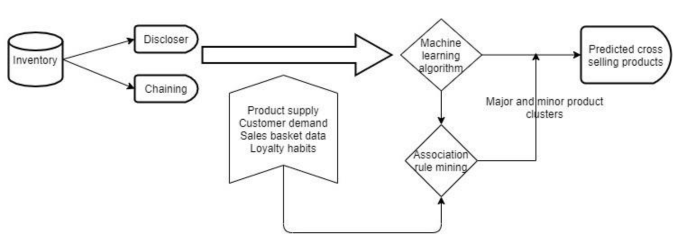

Figure 2: Cross selling model of the solution.

The predicted results of the algorithm after further processing with association rules, dependency among major product and minor products can be identified. These product clusters can be used in marketing and decision making related to customer retention. As a conclusion it can be stated that cross selling can be centrally used for the betterment of the retail industry via AI.

D. Retail marketing

Retail marketing helps to bring new customers to the business while maintaining a healthy relation with old ones. Retailers may need to consider various marketing strategies for the successful sales of different products and to communicate the value to their customers. The value and benefits differ with the marketing strategy. Some of the emerging marketing strategies with the implementation of AI in these strategies are discussed below.

Sentiment Analysis from product reviews

Online reviews play a significant role in the journey of customers to make a purchase and help the retailers in sales prediction [30]. Due to the abundant availability of the reviews, retailers are facing issues with information overload while mining the sentiment of these reviews [30]. Understanding the sentiment of these reviews may take a lot of time for an analyst, and the result may be biased based on the character of an analyst. Mixed reviews both positive and negative for a product can be widely found in most of the product reviews. This imbalanced sentiment in the reviews introduces significant problems while analysing these reviews. A study on sentiment mining approach found that improvement in the classification and prediction of these sentiments using the support vector machine (SVM), which is a supervised machine learning model [30]. It was found that although the SVM adjusted itself automatically well to data with imbalanced data, few of the results were influenced by the imbalanced sentiment. Rebalancing the data using under sampling and oversampling provided better results, but both of these methods also have their own limitations [30].

Marketing Coupons using revenue uplift model

The Uplift model not only predicts customers behaviour but also helps businesses to estimate the change in response behaviour in the customers from the marketing [31]. This helps the business to link their marketing action against the customer response and measure the impact of the marketing campaign. This paper investigated the implementation of the AI in an uplift model to support decisions in targeting campaigns using digital coupons. In 2018, among the 256 billion coupons distributed by US retailers over 1.7 billion coupons worth USD 2.7 billion were redeemed [18]. Coupons help customers to buy the product at a cheaper price or get some extra benefits. Distributing coupons to customers who were already looking to buy a product will decrease sales margin, so the retailers should find a targeting model to only distribute coupons to customers who have no intention to buy. The traditional response model only helps to predict customers buying nature, which cannot be very useful for targeting marketing [18]. With the implementation of AI for analysing customers data, the uplift model can help retailers to identify the targeted customers and predict the impact of coupons on customers buying patterns. Although the research and experiment on machine learning and uplift model carried on the profit decomposition for revenue uplift model, was limited to small business it displayed some sign of the success of this model [18]. The research material on this topic was limited and further research might help to get more insight into the benefits of an uplift model and causal machine learning.

Referral marketing on social media

Cashback is a new marketing strategy that is rapidly getting popular where anyone affiliated with the cashback can redirect customers to the business site where the customers will get a discount or return on their cash. Research done on machine learning approaches for predicting customer quality found that cashback marketing increased the loyalty of the customers to the business [14]. The paper described that the machine learning technique can be used to generate a predictive model which can predict customers behaviour using only the referrers data and information. Machine learning can be used to analyse the referrer data to provide personalized economic benefits based on the quality of new customers referred by them. The economic benefit encourages the referees to be more active on social media and encourages the fans to purchase more [14]. The analysis done by Vana, Lambrecht and Betini on the success of the cashback campaign showed that cashback payments increased the chances of purchases [17].

Current Implementation of AI in Retail Marketing

One of the areas in retail marketing where machine learning is found to be most widely used is the product recommendation system. Retailers have been using the recommender system to recommend a product to the users based on their previous and current transaction data. Margot is a machine learning-enabled chatbot that uses predictive analysis to recommend wines to its customers [33]. Amazon uses machine learning to suggest products to its customers based on the product the user is browsing and purchase history [33]. AI is currently used for cluster analysis which helps to identify a new group in the data [34]. "84.51" the analytics and marketing company of "Kroger" an American retail company is using machine learning to segment customers based on demographics, preference and buying behaviour [33]. This segmentation of customers is helping the company to create more personalized communication channels.

E. Real time data analytics

Real-time data analytics can process and analyze data instantly captured through visual sources (Image/video). It can keep an eye on the in-store activities and take necessary action instantly to improve customer service and can help retailers to manage their store more efficiently. Following are some use of real-time data analytics using the image and video data in retail:

Visual Market Basket Analysis (VMBA)

Nowadays retails have a presence both in-store and online. For online it is possible to understand consumers instantly based on their purchase and site navigation. But it is a bit challenging to perform that type of understanding in-store. Visual Market Basket Analysis can provide similar types of facilities in-store where data can be captured and processed instantly. Videos processed with algorithms can be transformed to customers' behaviours by dividing into three different high-level behavioural categories: action (stop vs moving), location (indoor vs outdoor), and scene context (cash desk, retail etc.) and further divided into 14 behaviours (from high-level behavioural categories) [21]. Among 14 behaviours, customer movement and pickup of the product-related behaviours can be the main source to perform VMBA.

Shelf Out of Stock (SOOS)

The global average out-of-stock rate is about 8%, and this leads to about 4% losses in sales for retail [22]. For the improvement of profits in continuous fashion retail stores should increase sales opportunities. It is possible to monitor the shelves in retail stores using a surveillance camera for maintaining high on-shelf availability. The fundamental concept here is to identify the change on the shelf by analysing an image such as increases/decreases in product amount [23]. Another way of doing this is to use a robot and store heatmap [22]. This concept also can be used for promotional activities (out of scope for discussion in this paper). Applying above concepts supported by machine learning algorithms it is possible to improve retail SOOS (Shelf out of stock).

Visualize hot spots (by real time count of people)

Visualizing the hotspots (areas inside the store where customer density is high) by counting people inside the store (real-time) can be beneficial for retails [24]. This can be used for the understanding of customer's traffic flow inside the store. This technique of creating hotspot based on captured images can improve retail customer service and it may support other techniques that can improve SOOS [22] providing heatmap.

Customer facial sentiment analysis

Customers express their sentiment many ways and it is not possible to get a clear customer sentiment from the transactional system alone. Customer Facial expression can be a good source to identify customer satisfaction. An automated approach can be applied to obtaining customer information using image processing and deep learning to classify facial sentiment [26].

In general terms, the technological requirement is very simple for the uses of real time data analytics described above. The main requirements are data capturing devices and machine learning algorithms to analyze captured data. Data can be sourced mainly through computer vision techniques (using fixed and surveillance cameras) and other types of technology like smart mobile, Radio Frequency Identification (RFIDs), real-time locating system (RTLS) can be used in this regard [25].

Data can be analysed using a range of machine learning algorithms that include mainly CNN (Convolutional Neural Networks) and Deep Convolutional Neural Networks (DCNNs). For example, GoogleNet can be used as a Convolutional Neural Networks platform [26]. Also, other machine learning algorithms like KNN (K-nearest neighbours), SVM (support vector machine), Decision Tree, Random Forest, Naive Bayes can be used to measure and compare the performance with CNN and DCNN [22].

V. INTEGRATED SOLUTION: CUSTOMER CENTERED AI ASSISTANT IN STORE

Following is a diagram (Figure 3) which summarizes the findings explained in the previous subsections of findings. Into the diagram it can be seen that all the sub sections contribute for the final solution in different aspects in retail.

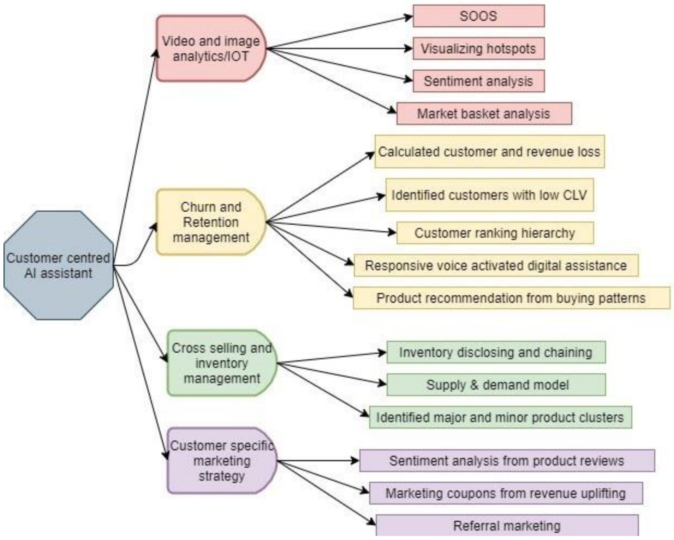

Figure 3: High level diagram of the final solution.

As per above figure the AI assistance will begin from the video and image analysis of the customer via IOT devices, surveillance cameras. Sentiment analysis and market basket analysis and SOOS (Shelf out of stock) will be conducted from that. The data collected during that phase will be forwarded to customer churn detection and retention units. Retention and churn units can do the processing and identify potential churn and measures which can be done to retain those customers. Together with data collected over a period with respect to customer loyalty purchasing and buying patterns the retailer can decide which customers should be prioritized to provide better customer satisfaction. The data collected from both customer purchase history and real time data will be used to perform customer retention measures. One such measure is product recommendation from time to time if the customer is hesitating to buy the product.

On the other hand, in order to maintain the inventory chain inventory disclosing will happen considering both product supply and customer demand for a particular product. In addition to that relationships among major products and minor products will be used to predict the possible product clusters. These minor products can be promoted as cross products alongside the major and popular products. Marketing strategies such as marketing coupons/ social referencing can be used at this level to promote such minor products which are less popular yet profitable to the retailer as well as useful for the customer.

Likewise, the interconnection among the operations and sub sections considered under the research can be elaborated.

VI. DISCUSSION

The research questions addressed in the selected methodology can be mainly categorised into five sections which are customer churn, customer retention, cross selling, marketing. According to the literature review there were many ways to implement sales operations in retail operations but not focused on customer centred operations. The research aimed to explore the measures as in how to overcome the challenges of operating interactive customer management based on retention and churn with the help of marketing cross selling products and tracking the customer sentiments using IOT. Findings from the literature review prove that there are sufficient resources(literature) to create the background to address the issue of implementing a customer-based solution. Technologies such as IOT using image capturing and processing, recurrent neural networks, machine learning, association rule mining were discovered as the techniques and tools to implement the solution.

Considering the role of AI in customer retention, some huge benefits make it different from traditional approaches. AI plays a huge role in collecting information using IoT and analysing behavioural patterns and predicting the habits of customers using predictive analysis changes the whole angle of managing customer relationships. Because AI can predict consumer decision-making patterns, it is a huge advantage on the side of the firms. Machine learning algorithms can be used to identify the needs and wants of customers and offer customers relevant products and alternatives quickly. Algorithms do a better job of providing the right product at the right time than a human employee. So, consumers' trust is increased in the firm and they are more likely to rely on suggested products than searching.

This development builds an advantage over time. The more a customer uses these features and the more it becomes a habit, and the person becomes to continue purchasing from the same firm. The better the firm can learn the individual's needs and preferences, and further use this information to strengthen the habit. Using multilingual and AI-based chatbots also gives a huge advantage to a firm because there will not be any language barriers and the customer service will be available 24/7 without failure. So, AI chatbots have a huge advantage over an online chat managed by employees. Machine learning is used to enhance customer relationships in personalized customer experience, Loyalty programs, and advertising campaigns to create superior recommendations to develop existing relationships and increase customer retention.

However, there are some disadvantages as well. Data from customers who do not have a customer profile, or a loyalty card are hard to collect. And the investment for IoT devices such as RFID (Passive RFID and medium density RFID) tags and high-tech cameras as well as software with machine learning algorithms can be expensive [2]. But the value the investment gives to the overall performance of a firm and the retention of customers is tremendous.

Comparing the use of traditional reporting techniques of churn analysis to predictive modelling two major decision-making performance benefits can be seen. One improvement stem from the capability of predictive models and data mining to account for more than one covariate at a time, which reduces the need to separately analyze customer and revenue churn. Likewise, this allows business to investigate the importance of other features available at once, reducing analysis times from manual feature selection and provides a single comprehensive model from which decisions can be made. Previous literatures have applied this methodology with transactional data to see if additional covariates outside of the RFM context can provide additional model accuracy. While monetary, service failure and socioeconomic status are just some of the tested features that have been found to have only minimal impact predictions [6]. Two derived attributes that correspond to the diversity and loyalty of customers with spending over changes in location and time have shown positive contributions to churn prediction. Being more important their base variables [35]. These examples show that business can comprehensively decide what data is needed to be kept for churn analysis, identifies potential areas associated with the features to focus retention strategies on which directly affects customer engagement with the business, and even experiment with new features to improve predictions. The other improvement is on prediction accuracies that can be obtained with the use of more sophisticated models compared to simpler RFM models as was found in research amongst the literature review. This can have a significant impact on the business's profits (especially in the case of subscriptions), as a slight percentage decrease in churn rate can mean an exponential increase to revenue when factoring in size of the customer base and subscription cost per customer. Thus, from the recommendations of other literature, AI based techniques should be used based on their potential to better model different predictors. And especially due to the potential that ANN and SVM with proper tuning can achieve far better results than logistic regression which is already commonly used for predictions [9][36].

In terms of cross selling which can be promoted based on historic and real time as mentioned under findings data of buying patterns, shopping basket and inventory. Hence, sales and products with less demand can be promoted [37]. At this phase inventory disclosure [11] which was discussed in literature review under cross selling will expose the challenges of constant commitment of the retailer. But that issue will not be addressed via this research since it is not a customer centred issue rather the retailer centred issue. Other challenges identified under promotion of cross selling are identifying the proper marketing strategies while reaching the right audience and maintaining healthy customer relationships while promoting optional products to the customer as it compromises the customer needs. Suggestions made by the prediction algorithm should meet the customer requirements in terms of product quality, purpose, and price. This is where association rules come in handy where minor items associated with major items can be used to suggest cross selling products. This will enlighten the fact that products with a large range can be used to proceed with the suggested methodology. With the historical data parallel buying can be customized.

The task to provide personalized marketing is complex and involves various factors including customer buying pattern, motives and need. As more and more customers are using technology, more and more data of both structured, transactional, and unstructured behaviour data of the customers are generated. The availability of various AI-enabled analytical tools has made analysing of this data easier and quicker [19]. AI with data analytics has enabled marketers to retrieve information on searched, abandoned and viewed products. The paper on big data and consumer behaviour discussed the possibility of identifying the search terms from search engines that attracted customers to a business [38]. This information can be used to highlight a customer's journey and build a profile that can be used by retail marketers to send personalized marketing offers.

Product purchase is the second phase of the marketing campaign that includes customer interaction with the business and products [19]. Collecting the data on this phase will be useful for profiling, demand forecasting and to evaluate the marketing strategy. Having a healthy communication and relation with the customers helps to increase customers' trust [19]. Use of AI in collecting and analysing the customer's journey and providing service and products that suit the customer's sentiments will help to build a healthier relationship. These trustful and healthy relationships can encourage customers to market the business and products through word of mouth, tweets and sharing pictures and videos of products.

Several uses of real time data analytics are introduced in this paper. Visual market basket analysis is one that understands a shopper's behaviour and their interaction with products (e.g., product pickup). As per experiment results (achieved through machine learning algorithm) individual visual features perform very well with high accuracies where overall best results were obtained by the DAGSVM (Direct Acyclic Graph Support Vector machine) approach, (accuracy of 87.71%). However, it was suggested future works in literature to do the experiment with the design of a framework based on deep learning (trainable in an end-to-end fashion). Also, suggested that the analysis needs to be extended to data collected in more retail stores [21]. VMBA proposed a hierarchy of 14 behaviours of shoppers (from high-level behavioural categories) captured by camera. Some of those behaviours are based on outside of the store and how those are important to the VMBA is not clear. Also, it is not clear how VMBA will be integrated with traditional market basket analysis (performed from a transactional system). Moreover, in a general sense it seems expensive and very hard for maintenance as every physical shopping cart needs to be mounted with a camera and related devices.

Two real time data analytics techniques were introduced in the previous section that can improve retails Shelf Out of Stock problem [22][23]. First technique that was able to correctly detected increases/decreases of the product amount in shelf was using fixed surveillance camera and convolutional neural networks machine learning classification algorithm. This technique was able to update the product amount using the classification results. Three experiments (using videos captured from a surveillance camera on the ceiling in a real store) were performed and output of the first two was convincing where the third one showed 89.6% accuracy [23]. Another technique used Rocky, a mobile robot that navigates and monitors store shelves based on real-time store heat maps to identify Shelf Out of Stock (SOOS) based on Deep Convolutional Neural Networks

(DCNNs). Two trained DCNNs were used to get visual and textual information and performance was compared with other classifiers like kNN, SVM, Decision Tree, Random Forest, Naive Bayes and Artificial Neural Network. Then, the two information were combined with a fusion classifier. The average for both kNN and SVM provided the best results for all possible visual and textual feature extractors. However, the performance of the overall content classification is higher (F1-score=.868) than the performance of the single visual (F1-score=.857) and textual classification (F1-score=.609). It was suggested that combining textual and visual information shows better performance; future works may need to improve the design of a new DCNN. It was also suggested to do more experiments in the future in different stores (with larger dataset) around the world [22].

Real time people count and visualize hot spots is one of the important uses of real time data analytics. Only a low-cost surveillance camera is required. This experiment was presented with a four-channel image representation named RGBP (red, green, blue, people). Several experiments were performed to validate, evaluate, and compare using a dataset (videos from a camera). Convolutional Neural Networks achieved high accuracy as almost all predictions contain less than 10% error. Main limitation identified that a trained model cannot be applied in different places or viewpoints of the same place. So, training modules need to customize. Another limitation of this experiment is it cannot separate employees from customers, so future work required in this regard [24].

Customer sentiment can be extracted from their facial expression using the image/video of the customer. A range of convolutional neural networks (CNN) were used to determine the individual's sentiment including customer gender and age. The presented system can be used to new and repeat customer identification, blacklisted customer warnings, and facial sentiment classification. This experiment included Face Detection, Face Recognition (accuracy of 97.65%.), Gender Classification (accuracy 87.02%), Age classification (accuracy 74.44%-, 79.9%), Emotion Classification (accuracy 87.36%). This experiment concluded that customer identity, gender, and emotion modules perform well however age modules. So, the age module needs some improvement. This experiment also raised concerns regarding the privacy and rights of individuals as the use of cameras in a public area [26].

All the experiments regarding visual data analysis were done in a real-world scenario and produced very good results (good accuracy or less error rate for classification algorithm). However, as we know there are different types of retail (it could be a grocery, fashion retail, pharmacy etc) so it is not clear that those experiments (real time data analytics) can be applied from a generalized point of view or need to customize for different types of retail. To get a clear picture more experiments need to be performed on different types of retails. The discussion regarding real time data analytics could not provide detail about how privacy will be preserved for visual data of customers. So future works need to focus on this (specially on privacy preserving data mining).This paper also suggesting that future work can be initiated to combine all the experiment regarding visual data analysis to produce a complete solution that will work side by side or in integrated fashion with others AI based system to aid retail to improve their services and operations.

VII. CONCLUSION

From the discussion above, it can be seen that retail businesses can achieve a lot of benefits by implementing AI in their business. The various areas of the retail business discussed in the paper suggest that the data collected and analysed using AI based techniques such as neural networks, association rule mining, recommendation systems and chatbots can bring huge benefits for businesses. It helps to make strategic decisions that increase profits, decrease operating expenses, and also improve customer satisfaction by providing more personalised services and reducing the frustration from SOOS problems.

There are many retailers like Amazon and Walmart who have already implemented machine learning and are differentiating themself to the customers. There are still many retailers who have yet to try to invest and implement machine learning. In the future, it will be interesting to research whether the success of a successful company was in any way related to early implementation of AI.

Although there are many other benefits of implementing AI, the retail business should also focus on having a secure system where data privacy is of high priority. Global retailers should understand and comply with the rules and regulations of the local country and community they trade in. For each subsection it was noticed that there are limited resources available for a specific sub area in retail even though there are many sources available for retail as in general. Therefore, it can be stated that customer centred retail assistance is an area which needs more attention in terms of future research.

Two drawbacks of implementing AI in retail is the initial cost, lack of literature and experience around how best to tune AI models for specific problems in different retail sectors to achieve better results than traditional approaches. There will be a considerable cost for the IoT devices and the machine learning software. This is an investment for the betterment of the company. But some firms may not have the financial capability, technical expertise, and option to use AI over traditional and more researched practices to invest such an amount of money into research and development such as start-ups. But the investment is worth it in the long run.

Further studies on the relationship between customer journey, data analytics and AI will help to deeply understand the constraint that retailers may face while implementing AI. Further research on the technologies and tools that are used to collect and analyze data will help to develop knowledge and solutions to solve complex problems of other industries.

VIII. Appendix One

Table I: Teammate weightings.

Participant	Weighting
Bijay	1
Darika	1
Hasan	1
Jinxi	1
Vindya	1
Total	5

All team members were active in meetings and collaborated in writing and discussing the final paper. As everyone had equal contribution in this research paper, we have decided to give the same weightings to everyone.

IX. Appendix Two

There was not enough information provided from our peer review and only grades for each category was provided. We have taken this in consideration and made following changes in the different criteria where we were graded low.

- The abstract and conclusion were edited to include more details about what was realized in the discussion.
- Number of headings was reduced and simplified to improve reading flow for easier understanding of the paper's theme.
- Literature review and methodology/findings have been edited to incorporate more reviewed literature into the development of our arguments.
- Conclusion was edited to provide more information about future research opportunities.

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