Exploring Social Contextual Influences on Healthy Eating using Big Data Analytics

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***Abstract*—An alarming proportion of the US population is overweight: 2/3 of US adults are overweight, and 1/3 of those overweight are obese. Obesity increases the risk of illnesses such as diabetes and cardiovascular diseases. This epidemic can be attributed to the combination of cheap, high-calorie food and lack of physical activity. In this paper, we propose a Big Data Analytics framework, called BiDAF, that aims to explore social contextual influences on healthy eating. For this purpose, we classified food tweets and social media images into as either healthy or unhealthy as well as food sentiments into either positive or negative, and further mapped them to an obesity prevalence map. The classification outcomes would be useful to reveal the social food trends and sentiments of the Centers for Disease and Control Prevention (CDC) USA obesity regions. The BiDAF framework has been implemented on Apache Spark and TensorFlow platforms. We have evaluated the BiDAF framework in terms of the accuracy on the food tweet classification and sentiment analysis. The experimental results indicated that the BiDAF framework is effective in classification and sentiment analysis of food tweet messages and also showed its potential in exploring social contextual influences that may contribute to healthy eating.**

I. Introduction

An alarming proportion of the US population is overweight: 2/3 of US adults are overweight, and 1/3 of those overweight are obese [9]. Already, one in six children in the US is obese, and one in three is overweight [20]. Obesity increases the risk of illnesses such as diabetes and cardiovascular diseases. This epidemic can be attributed to the combination of cheap, high-calorie food and lack of physical activity.

Twitter data have been popular used as a means for understanding trends in public health, such as tracking and understanding spreading diseases, e.g., influenza and cholera [2], [4], [6], [30]. The Center for Disease Control study reported that the trends like flu symptoms can be found from the tweet analysis [10]. The social data provided by 316 million Twitter users can be analyzed to understand their perspective and behaviors on health [18], [21]. Public behaviors, trends, preferences and their health lifestyle can be discovered from Analytics of social media data. Research with social media data may overcome the limitations of the traditional methods such as paper surveys or face-to-face interviews in health-related studies [10]. Furthermore, as social network users will be increased from 2.34 billion in 2016 to 2.95 billion in 2020 [35], the impact of Big Data Analytics with such social media data would be significant.

Big Data Analytics would be also capable of raising awareness about healthy behaviors for the general public and helping people develop healthy habits, such as choosing healthy foods or preventing obesity. The guidelines are already available through public health programs such as "Healthy Eating Made Easier" [34] and dietary guidelines for Americans [38]. MyPlate [38] reported that healthy eating style will be built throughout our lifetime and also be affected by personal and social factors such as our stage of life, situations, preferences, access to food, and culture.

Let us consider a scenario: *About 3 billion pizzas are sold annually in the U.S.* Super Bowl night is one of the most popular pizza nights of the year [32]. When people will make a chose of pizza brand and pizza toppings, they may ask questions such as *How many calories are in a slice of pizza?*, *How can I eat pizza and still lose weight?* Before making a decision, it is crucial to know about people's preference and food trends [36]. *62% of Americans prefer meat toppings. Women are twice as likely as men to order vegetables on their pizza. Crunchy thin crust is most healthy.* We can extend our questions to advanced Machine Learning (ML) tasks: *Has fast food in general had a big effect on obesity? Do obese kids become obese adults? Is your neighborhood full of 7-Elevens or Whole Foods? Are educated people more likely to go to full-service restaurants than to fast food franchises?*

Living in the era of social media, our decision on our foods may be strongly influenced by social trends. Our work is motivated by the works done in [15], [28], in which the relationships between obesity and food trends were found through Analytics with the Twitter data. We are interested in exploring the Big Data Analytics to understand the social trends of healthy eating and find the relation between obesity and food trends through analysis of social media data such as tweets and images. From the scenario, we know that Machine Learning (ML) can help detect healthy dieting statements (or food-related statements) in social media posts. *Is this particular tweet a healthy dieting tweet or not? What kinds of foods are indicators for healthy dieting? Are there any geographic tendencies in obesity problems? Does a tweet express a positive, neutral or negative sentiment about healthy* *dieting?* It would be meaningful to share our findings with public community and make them healthy choices such as ”look for food and drink choices that are lower in saturated fat, sodium, and added sugar,” and ”make healthy eating a part of their lives” [38]. We will expend the work done by Widener et al. [28] by mapping the geospatial food consumption trends and sentiment of food-related tweets to obesity prevalence in USA.

In this paper, we have presented a Big Data Analytics framework (called BiDAF), shown in Figure 1, for Twitter's food data classification and sentiment analysis. Our contributions of this paper are

- to develop a Big Data Analytics framework that analyzes Twitter data for classification of food types and food sentiments,
- to analyze the geospatial sentiment of tweets on healthy eating and map them onto the regions in the CDC's Obesity Prevalence Map [31], and
- to explore the Deep Learning Analytics for food image classification tounderstand the social food trends and obesity.

II. Related Work

A. Social Media and Machine Learning

Nguyen et al. [19] analyzed 80 million tweets using Machine Learning algorithms and build a national neighborhood database for well-being and health behaviors. Machine labeled as well as manually labeled tweets had a high level of accuracy: 78% for happiness, 83% for food with the F scores 0.54 and 0.86, respectively. The higher frequency of fast food tweets was posted from big cities. The frequency of tweets about fast food restaurants was higher than frequency of fast food mentions. Greater state-level happiness and positivity toward healthy foods, assessed via tweets, were associated with lower all-cause mortality and prevalence of chronic conditions such as obesity and diabetes controlling for state median income, median age, and percentage white non-Hispanic.

Eichstaedt et al. [7] analyzed Twitter messages using a regression model to find markers of cardiovascular mortality at the community level through the analysis of psychological correlates of mortality and demographic, socioeconomic, and health risk factors (e.g., smoking, diabetes, hypertension, and obesity). Their results showed that the Twitter-based model for predicting mortality outperformed classical risk factor based prediction models.

B. Machine Learning for Visual Food Recognition

Chokr et al. [3] presented a supervised machine learning approach to predict the amount of calories in a food item in a image, by a pipeline approach of identifying the type of the food item, estimating the size of the food item in grams, and predicting the amount of calories in the item. Liu et al. [16] developed a food recognition system using novel Deep Learning-based visual food recognition algorithms and outperformed existing work in terms of food recognition accuracy with reducing response time and lowering energy consumption.

Singla et al. [26] classified food or non-food images and food category recognition using the GoogLeNet model based on the deep Convolutional Neural Networks. They used three different data sets, which are Food-5K, Food-11,and IFD (Instagram Food Dataset). They reported 99.2% accuracy on the food or non-food classification and 83.6% accuracy on the food category recognition. Pouladzadeh et al. [24] specified the several types of calorie measurement of daily intake. Among discussed methods, they presented CNN with VBM (Visual Based Measurement) given satisfactory results.

Kagaya et al. [13] used the Food-Log (FL) mobile application for recognition of the food images and achieved 93.8% accuracy with Convolutional Neural Networks deep learning technique and 6-fold cross validation. Two category classifier (Food or Non-Food) was built using food images from Instagram data, Food-101,and Caltech-256 [14]. In this work, a deep Convolutional Neural Networks method was used and 96% accuracy for Instagram data, 95% accuracy for Food-101 and Caltech-256 datasets were achieved. Farinella et al. [8] used Anti-textons representation to classify the food images of UNICT-FD1200 dataset (having 8 categories of manually labelled food images) and achieved 85.82% accuracy.

C. Social Media and Health and Sentiment Analysis

According to the report of Centers for Disease and Control Prevention (CDC) [31], young adults were half as likely to have obesity as middle-aged adults. Adults aged 18-24 had the lowest self-reported obesity (17.3%) compared to adults aged 45-54 years who had the highest prevalence (35.1%). Thus, the social media analysis may be useful for obesity awareness and promoting healthy eating. Paul et al. [22] presented the Ailment Topic Aspect model to analyze Twitter messages and to measure behavioral risk factors by geographic region for some medical conditions like allergies, obesity and insomnia. They concluded that Twitter can be broadly applicable to public health research. Madan et al. [17] studied about the relationship between social interaction and healthy related behaviors such as diet choices or long-term weight changes using sensing and self-reporting tools. Scanfeld et al. [25] analyzed Twitter data about antibiotics and determined the categories of antibiotics such as cold and antibiotics, flu and antibiotics, leftover antibiotics.

There are several works on sentiment analysis with food tweets. Sentiment analysis aims to determine whether a feature of a tweet is positive, negative, or neutral. Poria et al. [23] presented an innovative method to extract features from textual and visual datasets using deep Convolutional Neural Networks. With the use of those features and a multiple kernel learning classifier, they achieved the state of the art of multimodal emotion recognition. Go et al. [11] trained on one million tweets in the food domain for sentiment analysis for Twitter and achieved accuracy of 83%. FoodMood [5] analyzed tweets for a food sentiment and social, and cultural aspects using Bayesian Sentiment classifier. Interestingly, they

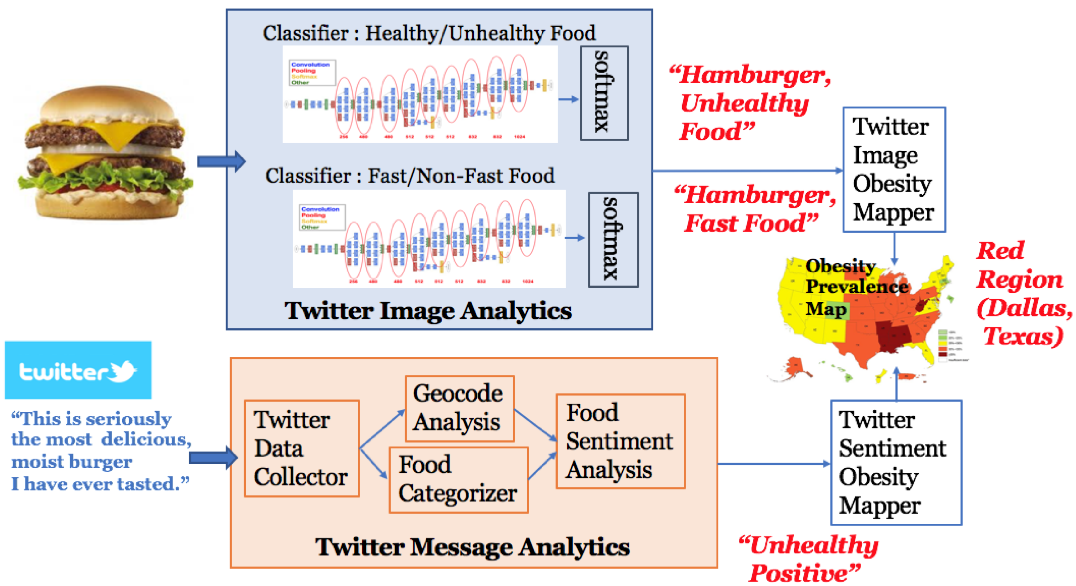

Fig. 1. BiDAF Framework

indicated constantly evolving food trends (e.g., meat or fast food sentiment). However, there is room for improvement in utilizing diverse data such as tweet messages and social images, to find relationships among food, sentiments, location, and obesity. In addition, real-time Analytics and interventions are not yet available for real-world applications.

III. BiDAF: Big Data Analytics Framework

The BiDAF framework is a hybrid model of shallow learning and deep learning for tweet message/image classification and sentiment analysis. The primary models include the Analytics tasks as follows:

1) Tweet Food Message Analytics
   - Twitter Food Item(s) Frequency Analysis
   - Food Classification (Healthy or Unhealthy)
   - Food Tweet Sentiment Analysis (Positive or Negative)
   - Tweet Classification with Four Categories (Healthy-Positive, Unhealthy-Positive, Healthy-Negative, and Unhealthy-Negative)
   - Geospatial Mapping between Food Categories and Obesity (Obesity Prevalence Regions in USA)
2) Tweet Food Image Analytics
   - Food Image Recognition
   - Food Multi-Object Recognition
   - Healthy/Unhealthy Food Image Classification
   - Fast Food/Non-fast Food Image Classification

A. Food Tweet Message Analytics

For the tweet message Analytics, the operations have been conducted as follows: First, the real-time tweet data is collected for the food analysis using the Twitter streaming API [37]. Second, the tweets are tracked from the selected locations of Twitter users (refer to Table III) and filtered by providing the healthy or unhealthy food keywords (refer to Table I). We mapped the location of Twitter users (i.e., geocodes) into the Obesity Prevalence Regions using the bounding box service[33] and all tweets we collected are now annotated with the city and state of tweet's users. Third, the frequency of food items was counted for each tweet and then each tweet was classified either healthy or unhealthy. After applying Term Frequency on the collected Twitter data for the healthy/unhealthy categorization, the food sentiment analysis will be conducted on the healthy food categorized tweets. For the sentiment analysis of tweets, we used Valence Aware Dictionary and sEntiment Reasoner (VADER) that is a lexicon and rule-based sentiment analysis tool [12], specifically attuned to sentiments expressed in social media. The VADER reasoner handles slangs, emoticons, acronyms, contractions, and punctuation to increase a more accurate analysis of sentiments in the tweets. The compound score is calculated by adding the valence scores of each word present in the tweet, and then adjusting scores measured on between -1 (highly negative) and +1 (highly positive) according to the rules. The category of tweet sentiments is defined by the compound score as follows:

- positive sentiment: compound score $\geq$ 0.52.
- neutral sentiment: (compound score $>$ -0.5) and (compound score $<$ 0.5)
- negative sentiment: compound score $\leq$ -0.5

Then, a tweet is determined as a negative tweet or a positive tweet by the averaging of positive, negative, and neutral sentiments. Interestingly, ”eating green grapes” is classified as a neutral sentiment. In this paper, we take the neutral sentiment as positive as we want to find the negative/positive eating trends of the users.

B. Food Image Analytics

For the food image classification, we have designed a two-level classification:

- The bottom level classification model has two classifiers
  - a classifier with 23 healthy/unhealthy food items (Table VII)
  - a classifier with 20 fast/non-fast foods (Table VIII)
- The top level classification model has two classifiers
  - a classifier with two classes, i.e, Healthy food and Unhealthy food
  - a classifier with two classes, i.e, Fast food and Non-fast food

The bottom level models are designed using the pre-trained Inception v3 model [27] to classify food images into twenty three food classes (as shown in Table VII) as well as into twenty food classes (as shown in Table VIII). The Inception model used in the bottom level models (shown in Figure 1) has 11 convolutions together with the expensive 33 and 55 convolutions. A 1x1 convolution was designed with 128 filters for dimension reduction and rectified linear activation. An average pooling layer was designed with with 5x5 filter size and stride 3. A fully connected layer was designed with 1024 units and rectified linear activation. A dropout layer was designed with 70% ratio of dropped outputs. Besides being used as reductions, we also include the use of rectified linear unit (ReLU) activation which makes them a dual-purpose. A linear layer was designed with softmax loss as the classifier. The Inception model was designed to introduce an optimal local sparse structure that can be approximated and covered by readily available dense components in a Convolutional Neural Network (shown in Figure 1).

The Inception model has millions of parameters and can take weeks to fully train. We utilized a technique called Transfer learning to train our model quicker. Transfer learning is a technique that takes a fully-trained model for the food categories selected from ImageNet, and retrains from the existing weights for the food categories (refer to Table VII and Table VIII). In this project, we retrained the final layer from scratch, while leaving all the others untouched. The width of the Inception modules ranges from 256 filters (in early modules) to 1024 in the top Inception modules. The number of parameters is reduced to 5 million. The top level models are based on a linear layer with softmax loss as the classifier for two kinds of binary classes such as Healthy/Unhealthy Food or Fast/Non-fast Food.

IV. Experimental Results

A. Tweet, Food and Obesity Dataset

We collected tweets from the Centers for Disease and Control Prevention (CDC) obesity prevalence regions across the United States, determined the content of diet tweets, their location, and sentiment analysis of the tweet messages (e.g., the relative frequency of sentiments in terms of positive and negative) for each state in US. We correlated these community-level healthy food trends with obesity prevalence across states & territories obtained from the CDC [31].

For Twitter message analysis, we used the Healthy/Unhealthy food categorization (75 healthy foods and 37 unhealthy foods) as shown in Table I, defined by the USDA MyPlate (2015-20 Dietary Guidelines for Americans for children) [38] and USDA Standardized Recipe [39]. As expected, fruits and vegetables are classified as a healthy food and fast foods are classified as a unhealthy food.

TABLE I
Healthy Foods & Unhealthy Foods

Healthy Food Keywords
1. apple juice 2. apples 3. apricots 4. bananas 5. blueberries 6. cantaloupe 7. cherries 8. fruit cocktail 9. grape juice 10. grapefruit 11. grapefruit juice 12. grapes 13. honeydew 14. kiwi fruit 15. lemons 16. limes 17. mangoes 18. nectarines 19. orange juice 20. oranges 21. papaya 22. peaches 23. pears 24. plums 25. prunes 26. raisins 27. raspberries 28. strawberries 29. tangerines 30. watermelon 31. acorn squash 32. artichokes 33. asparagus 34. avocado 35. bean sprouts 36. beets 37. black beans 38. bok choy 39. broccoli 40. brussels sprouts 41. butternut squash 42. cabbage 43. cassava 44. cauliflower 45. celery 46. collard greens 47. cow peas 48. cucumbers 49. dark green leafy lettuce 50. eggplant 51. field peas 52. zucchini 53. white beans 54. watercress 55. water chestnuts 56. turnips 57. turnip greens 58. tomato juice 59. taro 60. sweet potatoes 61. split peas 62. spinach 63. soy beans 64. romaine lettuce 65. red peppers 66. plantains 67. pinto beans 68. okra 69. navy beans 70. mustard greens 71. mushrooms 72. mesclun 73. lentils 74. kidney beans 75. hubbard squash
Unhealthy Food Keywords
1. bacon 2. cake 3. cheese 4. cookies 5. donuts 6. energy drink 7. fruit drink 8. hot dogs 9. ice cream 10. pastries 11. pizza 12. sausage 13. soda 14. Arby 15. Baskin Robin 16. Boston Market 17. Captain D 18. Chick-fil-A 19. Chipotle 20. Del Taco 21. Dunkin Donuts 22. Domino Pizza 23. Five Guys Burger & fries 24. Hardees 25. KFC 26. Krispy Kreme 27. McDonald 28. Panda Express 29. Pizza Hut 30. Starbucks 31. Wendy 32. Papa Johns 33.french fries 34.fried chicken 35. beer 36. bread 37. beef burger

The CDC presented prevalence maps of adult obesity categories according to geographical regions (refer to Table II and Figure 2) [31]. The prevalence of obesity among U.S. adults was computed based on self-reported information by state and territory in 2016. Unfortunately, all states in USA had more than 20% of adults with obesity. The South had the highest prevalence of obesity (32.0%), followed by the Midwest (31.4%), the Northeast (26.9%), and the West (26.0%).

B. Twitter Classification & Sentimental Analysis

We obtained a sample of 1588 tweets collected in September, 2017. These tweets are classified by Twitter users' self-

TABLE II
Obesity Prevalence (OP) in 2016 Across States & Territories

Region	Adult Population	State
Green	$20\% \leq OP < 25\%$	Colorado, Hawaii, Massachusetts, DC.
Yellow	$25\% \leq OP < 30\%$	22 states and Guam
Orange	$30\% \leq OP < 35\%$	20 states, and Puerto Rico, Virgin Islands
Red	35% or more	5 states (Alabama, Arkansas, Louisiana, Mississippi, West Virginia)

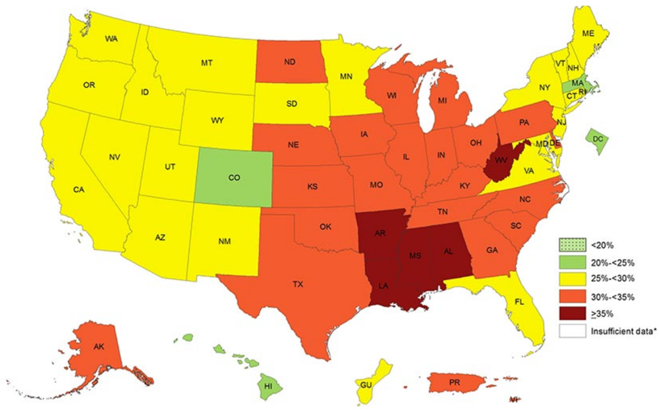

Fig. 2. Obesity Prevalence in 2016 Across States [31]

reported locations in their user profiles, and we used this information to map these tweets to the ten states randomly selected from the four regions in USA (Green, Orange, Red, Yellow) of the CDC obesity prevalence map in Table III. For details, see the mapping tweets to US states of the CDC Obesity Prevalence Map [31]. The tweets from the four different regions in the Obesity Prevalence Map were classified as one of four categories such as Healthy-Positive, Healthy-Negative, Unhealthy-Positive, and Unhealthy-Negative.

From the sentimental analysis, those 1588 tweets from the states of the CDC obesity prevalence map were classified as 81% positive and 19% negative. We also categorized them in terms of four healthy food sentiment categories (as shown in Table IV). As we expected, Unhealthy-Positive (63%) is the highest food sentiment type, followed by Healthy-Positive (18%), Unhealthy-Negative (15%), and Healthy-Negative (4%).

TABLE III
CDC Obesity Prevalence Map

Green Region	Orange Region	Red Region	Yellow Region
Colorado	Illinois	Mississippi	Washington
Massachusetts	Kansas	Louisiana	California
District of Columbia	North Carolina	Alabama	New York
Hawaii	Texas	Arkansas	Arizona
	Missouri		Minnesota
	Ohio		Utah

TABLE IV
Healthy Food Sentimental Analysis

	Healthy		Unhealthy		Sentiment	
	#Tweet	Tweet%	#Tweet	Tweet%	#Tweet	Tweet%
Positive	285	18%	1002	63%	1287	81%
Negative	57	4%	244	15%	301	19%
Total	342	22%	1246	78%	1588	100%

Figure 3 shows the tag cloud of four obesity prevalence regions (Green, Yellow, Orange, Red) from the food tweet sentiment analysis. Each region shows 15 to 20 food words. The tag cloud depicts frequently mentioned food keywords and the importance of each tag is shown with its font size or color. A bigger tag is a more frequently mentioned food keyword compared to a less frequently mentioned one in a smaller tag. The green region shows healthy foods (e.g., Spinach and Broccoli) while the red region has more unhealthy foods (e.g., Pizza and Beer). Table V shows some examples from the four food sentiments: Healthy-Positive, Healthy-Negative, Unhealthy-Positive, and Unhealthy-Negative. There are some challenging cases, for example for automatic sentiment analysis, the following tweets are classified as Healthy-Negative: *I'm eating stuffed salmon with broccoli; i've never been more satisfied by food in my life.* and *he just ate mushrooms for the first time swear.* The first case is an extremely positive expression and the second one is implicitly expressed a positive sentiment.

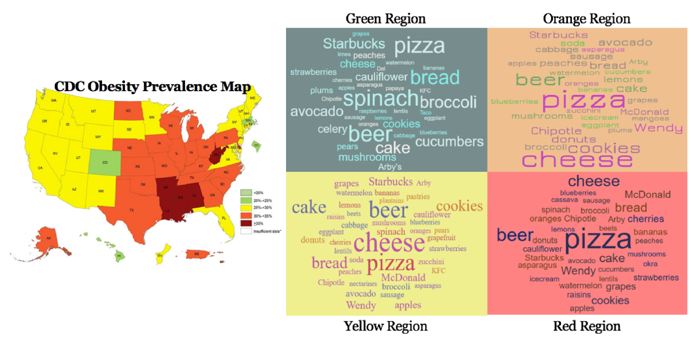

Fig. 3. Tag Cloud for Food Tweet Analysis on CDC Obesity Prevalence Map

TABLE V
Examples of Healthy Food Tweet & Unhealthy Food Tweet

Healthy Positive Food Tweets
"This Thai spinach, brown rice is wonderfully aromatic and delicious."
"A ginger, lemon, orange and grapefruit juice is the best thing whenever I get cold symptoms."
"Another delicious salmon dish from my dear friend Linda"
Unhealthy Positive Food Tweet
"Cake or pie? Can I choose both?"
"I love eating chocolate cake and ice cream after a show."
"A other beer in bed. Yes please!"
Healthy Negative Food Tweet
"I am sick of eating broccoli. I also hate spinach."
"Tomato? Yuk! We've got Tomato Mushroom Spaghetti."
Unhealthy Negative Food Tweet
"Ate a whole pizza now I hate myself"
"I love alcohol but if alcohol killed 88,000 people a year."
"I lovvvvvvve the Halloween cookies. I just wanna know why they made them so damn small"

C. Image Classification

The results of the top level food classification are shown for the Healthy/Unhealthy and Fast food/Non-fast food in Table VI. For the Healthy/Unhealthy classification, we used 12,873 Healthy food images and 8,602 Unhealthy food images collected from ImageNet. For the Fast food/Non-fast food classification, we used 11,859 Fast food images and 11,166 Non-fast food images collected from ImageNet. The food images of two categories (Healthy/Unhealthy & Fast food/Non-fast

TABLE VI
TOP LEVEL FOOD IMAGE CLASSIFICATION: HEALTHY/UNHEALTHY FOOD & FAST/NON-FAST FOOD

Categories	#Images	Categories	#Images
Healthy	12,873	Fast Food	11,859
Unhealthy	13,165	Non-fast food	11,166
Total	26,038	Total	23,025
Accuracy			
Train Accuracy	97%	Train Accuracy	94%
Test Accuracy	95.80%	Test Accuracy	96.80%
Validation Accuracy	98%	Validation Accuracy	96%
Cross entropy	0.105423	Cross entropy	0.1

TABLE VII
IMAGE CLASSIFICATION FOR FOOD 23 CATEGORIES

Healthy Food	#Images	Unhealthy Food	#Images
pears	1279	bacon	591
water melon	1353	hot dogs	1257
grapes	1684	sausages	79
cherries	1337	donuts	1314
bananas	1409	ice cream	994
cucumbers	1268	cheese	759
spinach	1108	cakes	69
kale	1191	pizza	1289
celery	1020	soda	1361
broccoli	1224	cookies	1242
		burger	1373
		chocolate	1350
		french fries	1487
Total	12,873	Total	13,165
Accuracy			
Train Accuracy	76%	Test Accuracy	78.30%
Validation Accuracy	77%	Cross entropy	1.242658

food) are partially overlapped. The data is divided into the 70% training data and 30% testing data. For testing, food images were also collected from tweets from the regions. The accuracy of 97% (training), 95.8% (testing), and 98% (validation) are obtained for Healthy/Unhealthy food classification and the accuracy of 94% (training), 96.8% (testing), and 96% (validation) for Fast food/Non-fast food classification. We will integrate two models into a single model in the near future.

The results of the bottom level food classification are shown for 10 Healthy food and 13 Unhealthy food in Table VII and for 10 Fast food and 10 Non-fast food in Table VIII, respectively. For the Healthy/Unhealthy food classification, 12,873 Healthy food images and 8,602 Unhealthy food images. For the Fast food/Non-fast food classification, 11,859 images for 10 Fast foods and 11,166 images Non-fast foods are used. For the Healthy/Unhealthy food classification, 76%, 78.3%, and 77% are obtained for training accuracy, testing accuracy, and validation accuracy, respectively. For the Fast food/Non-fast food classification, 82%, 80.4%, and 75% are obtained for training accuracy, testing accuracy, and validation accuracy, respectively.

The learning performances of the image classifiers are shown in Figures 4 - 7 as a learning graph with x-axis (epoch) and y-axis (accuracy). Figure 4 shows the learning performance in building the healthy food classifier. From the plot of accuracy we can see that the model could probably be trained a little more until 20 epochs as the learning accuracy on the dataset is still rising for the last few epochs. After 20 epochs, the accuracy is reached up to 97%. The overall accuracy is ranged from 94% to 98% for the epochs between

TABLE VIII
FAST FOOD/NON-FAST FOOD & 20 CATEGORY CLASSIFICATION RESULTS

Fast Food	#Images	Non-Fast Food	#Images
hamburger	1373	peaches	1230
french fries	1487	celery	1020
pizza	1289	kale	1191
pancake	843	chickpea	1237
hot dogs	1257	tunas	64
soda	1361	avocado	1346
bacon	591	broccoli	1224
donuts	1314	spinach	1108
chocolate	1350	bananas	1409
ice cream	994	cherries	1337
Total	11,859	Total	11,166
Accuracy			
Training Accuracy	82%	Test Accuracy	80.40%
Validation Accuracy	75%	Cross entropy	1.2

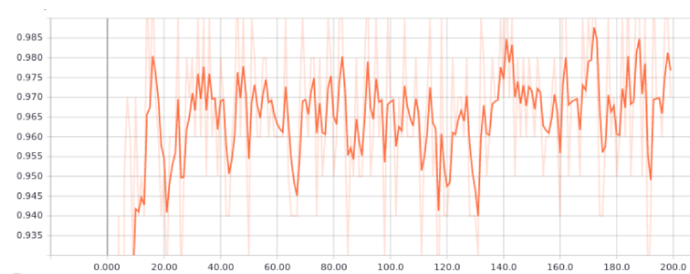

Fig. 4. Accuracy for Top Level (Healthy/Unhealthy) Food Image Classification

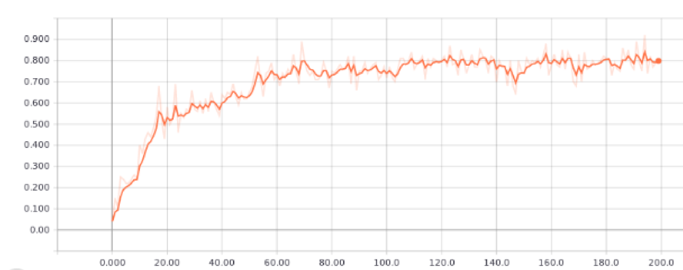

Fig. 5. Accuracy for Bottom Level 23 Food Items Image Classification

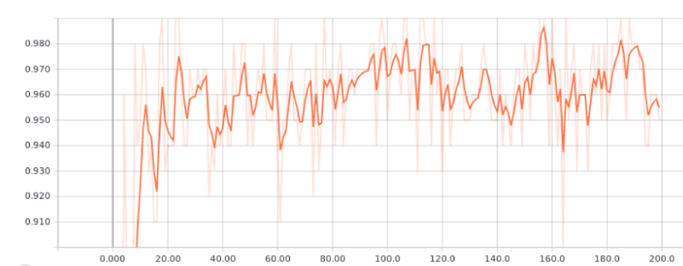

Fig. 6. Accuracy for Top Level (Fast Food/Non-Fast) Food Image Classification

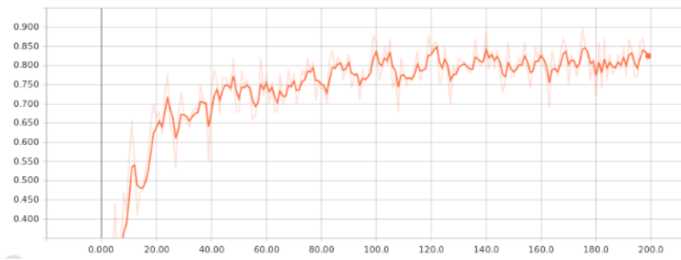

Fig. 7. Accuracy for Bottom Level 20 Food Items Image Classification

20 and 200. Figure 5 shows the learning performance in building the 23 food classifier. From the plot of accuracy we can see that the accuracy was raised up to 50% at epoch 20 and up to 75% at epoch 60. As shown in Figure 6 and Figure 7, the 20 Fast/Non-fast food classifier is slightly better than one for 23 Healthy/Non-healthy food classifier in Figure 4 and Figure 5, respectively.

The confusion matrix in Figure 8 shows the classification performance for the Healthy/Unhealthy food images. In this matrix, the actual labels of foods are shown in columns and the predicted levels of foods in rows. In this matrix, *graphs* are highly confused with *water melons* as well as *cherry* and *chocolate* are confused with *donuts* and *cakes*, respectively. The image classification of *Bananas* and *broccoli* show a high accuracy.

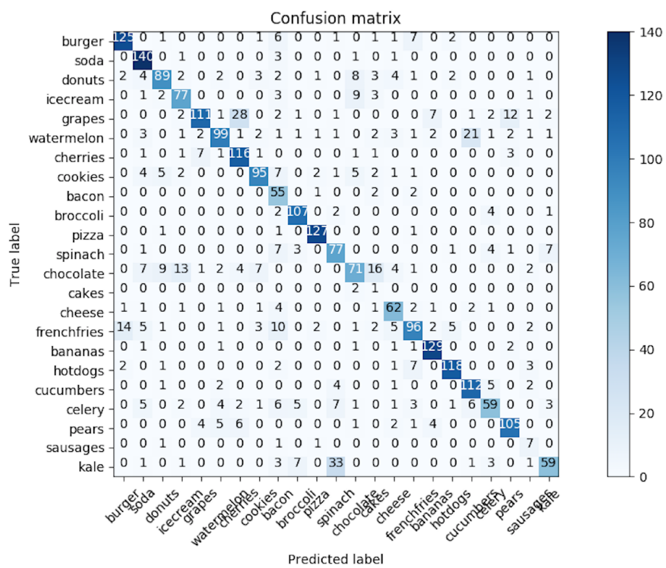

Fig. 8. Confusion Matrix for Healthy Food and Unhealthy Food Image Classification

The food classifier outperforms with the recognition of multi-items of food images. Figure 9 shows the recognition outcomes of Healthy food with multiple food items including *pears*, *graphs*, and *bananas*. In this model, *oranges* and *apples* are not properly recognized since these food items are not trained in the model (refer to Table VII). The bottom level classifier accurately identified multiple food items such as *cherries* (24%), *pears* (20%), *grapes* (19%), and *bananas* (5%) while the top level classifier recognized Healthy food with 99.6% confidence (refer to Table VII). Figure 10 shows the recognition outcomes of Fast food classification with multiple food items including *french fries*, *chicken*, and *chocolate donuts*. The bottom level classifier accurately identified *donuts* (15%), *french fries* (10%), and *chocolate* (9%) while the top level classifier recognized Unhealthy food with 96.1% confidence. In this model, *fried chicken* was not trained so that the food item was not recognized (refer to Table VIII). These results confirm that our food image classifiers are very effective in the recognition of multi-food items.

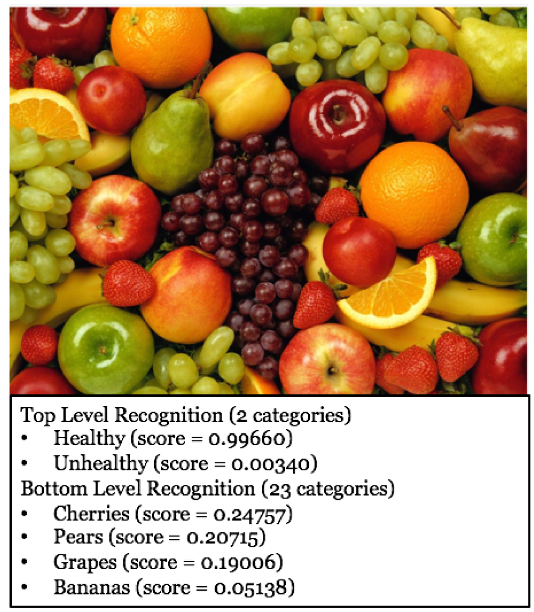

Fig. 9. Accuracy for Healthy Food Multi-Object Recognition

V. Conclusion

In this paper, we presented that a Big Data Analytics (BiDAF) framework is effective in the classification and sentiment analysis of tweets in terms of Healthy/Unhealthy food and Positive/Negative sentiments. In addition, the classified tweets were mapped to the obesity prevalence map and a food word cloud was captured for the four different regions. This confirms that BiDAF can be used to reveal social food trends or sentiments in the obesity prevalence regions in USA and understand the social food trends and obesity. The BiDAF framework has been implemented with Apache Spark [29] and TensorFlow [1]. We have evaluated the effectiveness of the BiDAF framework in terms of food tweet classification and sentiment analysis. The preliminary results show satisfactory classification and sentiment analysis, such as (1) a validation accuracy of 98% for Healthy/Unhealthy classification and a validation accuracy of 77% for classification of 23 Healthy/Unhealthy food items; (2) a validation accuracy of 96% for Fast/Non-fast food classification and a validation accuracy of 75% for 20 Fast/Non-fast food items. We conclude that the BiDAF framework has a potential in help us a better

Fig. 10. Accuracy for Fast Food Multi-Object Recognition

understanding of social media influence on our behavior and decision-making on healthy eating and obesity prevention.

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