Evaluating Sentiment on Demonetization via Heuristic Deep Neural Networks: The Sendemonnet Model

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Abstract: *This paper examines the multifaceted impact of demonetization in India and explores the role of sentiment analysis in gauging public reactions through social media platforms, particularly Twitter. Implemented in 2016, demonetization aimed to combat corruption, curb black money, and promote financial transparency. However, its execution led to substantial economic disruptions across various sectors, particularly affecting daily wage earners and small businesses reliant on cash transactions. This study uses Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs) to merge insights from economic analysis with sophisticated sentiment analysis techniques. By analyzing Twitter data, sentiment analysis uncovers a spectrum of public responses and emotional sentiments towards demonetization, revealing its profound societal impact beyond conventional economic metrics. CNNs excel in processing textual data, while DNNs handle both textual and visual inputs effectively, providing nuanced insights into public sentiment dynamics during a pivotal policy intervention. This research contributes to a deeper understanding of societal responses to economic policies in real-time, leveraging social media as a crucial tool for contemporary discourse analysis.*

Keywords: *Demonetization, Sentiment Analysis, Social Media, Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs)*

I. INTRODUCTION

One of the biggest economic developments of our time will be demonetization, which will be remembered by a generation. Any Indian citizen is affected by it. The undersigned is in favor of any initiatives aimed at combating corruption, outlawing black money and counterfeit money, and taking action against financial support for terrorism and other activities that sow discord and hatred among the populace. On November 8, 2016, at 8:00 p.m., Prime Minister Shri Narendra Modi declared that the 500 and 1000 currency notes will be devalued and that new 500 and 2000 notes would be introduced. This process is known as demonetization. Demonetizing the Rs. 500 and Rs. 1000 notes was an ill-considered move that won't address the problem of black money across the country. The country is currently experiencing a riot-like situation as a result of demonetization. Tax avoidance on both money earned from illicit activity and revenue from legal activity is the source of black money. Demonetization is a pointless endeavor if measures are not taken to prevent the creation of black money, as was the case in 1978. Demonetization as a cleansing strategy might have several positive effects on the economy. For the less fortunate members of society who rely on their daily labour to make ends meet and for those who lack access to digital transaction culture, it results in unavoidable welfare and financial losses. There will be a short-term slowdown in economic activity. On the other hand, long-term benefits like as more transparency and a decrease in the quantity of black money activities might be considered immeasurable [1].

The major economic event known as demonetization in India mostly affected the economy by disrupting liquidity. A significant shortage of cash resulted from the withdrawal of the Rs 500 and Rs 1000 notes, which made up 86% of the money in circulation. This reduced the usefulness of the Rs 2000 note as a transaction currency and created a significant gap in the composition of the currency. This liquidity shock hurt daily wage workers and small merchants who depended on cash in particular, and it had an impact on consumption, investment, output, employment, and overall economic growth. A decline in employment, output, consumption, and tax income were among the immediate effects, which could have hampered India's GDP development. Even while short-term bank deposits increased, long-term savings growth was not anticipated. Because a large portion of black money was stored in assets like gold and real estate, the impact on it was minimal [2]. Demonetization did, however, increase public awareness of the need to combat black money and fake currency. Even while it resulted in short-term economic disruptions and losses for the impoverished in terms of welfare, it fostered long-term advantages including more transparency and a decline in the activities of black money.

Social media has grown in popularity and is now regarded as a part of our lives due to the extensive usage of the internet. Twitter is widely regarded as the most popular social media platform globally, enabling users to exchange information and express their opinions through tweets. Users may also use Twitter as a platform to voice their feelings on any hot issue. Twitter users publish tweets, which the media uses to get statistical information on the public's opinions in real time.

Sentiment analysis may be used to determine how a Twitter user feels about a certain kind of tweet. Natural language processing (NLP) is a technology used in sentiment analysis to determine the emotional tone of the tweets. Natural language processing, or NLP, is one artificial means of having a conversation in natural language with an intelligent machine. Furthermore, by determining if the language is objective or biassed, sentiment analysis is an automated technique that helps manage the polarity of text data, which can be either text or an image. Determining the sentiment polarity of the tweets is the primary goal of sentiment classification in Twitter data. By examining the sentiments expressed in the tweets that are retrieved from Twitter, one may ascertain the public's views and reactions about various topics. Sentiment analysis is performed on the set of tweets from the Twitter API dataset in order to ascertain the polarity of the messages [3].

Sentiment analysis is the study of people's feelings, moods, affect, emotional states, and temperaments via the analysis of written language. Having a substantial sentiment investigation method is necessary in the big data age for several reasons, most notably for understanding emotions. These days, professional and even social broadcasting have been severely damaged by the influence of sentiment analysis. Social mass media has evolved so quickly that everyone in the globe may express their thoughts and emotional states online. Therefore, sentiment analysis is essential to comprehending customer or reviewer viewpoints. Moreover, sentiment analysis is an essential instrument for analysing the feelings that a community feels as a whole [4].

The increasing amount of information available in social media has made sentiment analysis more significant; pertinent research has been divided into three main application areas. From a commercial perspective, sentiment analysis may provide customers and businesses with online recommendations and advice. One way that e-commerce platforms might utilize the data is to analyze their products and services by using the customer preferences that are shown. The virtual nature of online shopping, however, might make it difficult to completely and objectively understand a product. It can also be uncertain whether a buyer is ready to learn about the comments or opinions of other customers. Another significant element from a political standpoint is the enormous need for political information. People search for or express opinions online for reasons other than commercial gain [5].

Surveys and questionnaires were used to first collect people's opinions, which were then personally examined. But when more people started utilizing the internet, more people started to express their thoughts there. The emergence of social media platforms in recent times has facilitated the wider dissemination of knowledge. Many academics use sentiment analysis using text, audio, visuals, and a mix of these to determine the sentiments. The most popular industries that use sentiment analysis or opinion mining are business, politics, and healthcare. Users of social media number in the billions. Reviews of various platforms provide rich data sources, including audio files, videos, images, and opinions. The two main pillars of NLP are sentiment analysis and emotion identification. These two names have several important differences, despite the fact that they are sometimes used interchangeably. With sentiment analysis, one may ascertain if a piece of data is positive, negative, or objective. On the other hand, emotion detection is the identification of certain human emotions like pleasure, happiness, sadness, or rage. At times, it's possible to use "emotion analysis," "emotion detection," and "emotion identification" synonymously [6].

I. HEURISTIC METHODS IN NEURAL NETWORKS

These days, feed-forward neural networks are the go-to method for solving regression and classification issues. A neural network's architectural structure, layer activation functions, and training process are among its constituent parts. These elements have a significant impact on a neural network's performance, and while several methods have been put out recently, choosing an appropriate value for these parameters remains a contentious process. Neural networks are widely utilized in industrial applications because they lessen the effort needed for decision makers to obtain the knowledge needed to make the right judgments about processes. However, the restricted dataset dimension that may be applied to network training penalises the full industrial issue applicability of the NN technology [7].

Gottfried Leibniz is credited with introducing artificial intelligence (AI) through his theories and thoughts. McCulloch and Pitts' evolutionary model of the human brain served as the impetus for the 1943 research of artificial neural networks (ANNs). ANNs have the ability to recognise, understand, and solve a broad variety of challenging issues. The most popular and commonly utilised machine learning (ML) algorithm techniques nowadays are artificial neural networks (ANNs) and deep learning (DL) methods [8].

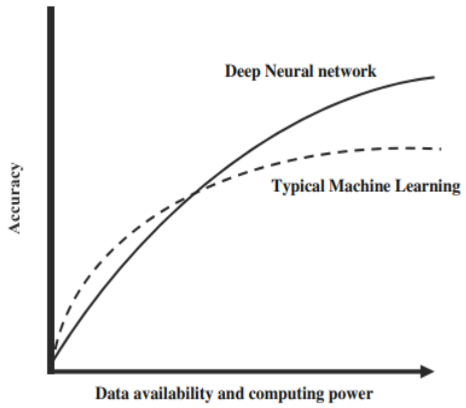

Figure 1: Comparison of the Accuracy of a Typical Machine Learning Algorithm and a Deep Neural Network [8]

The accuracy of a deep neural network (DNN) and a standard machine learning technique are contrasted in Figure 1. It is clear that when sufficient data and processing power are available, deep learning algorithms perform more accurately than classical machine learning techniques.

II. DEEP LEARNING TECHNIQUES IN SENTIMENT ANALYSIS

Many models, particularly the recently enhanced deep learning models, can perform sentiment analysis jobs successfully. Convolutional neural networks (CNN) and deep neural networks (DNN) are two examples of these models.

A. CONVOLUTIONAL NEURAL NETWORK

CNNs and regular neural networks are nearly identical. CNN neurons receive an input, analyze it, and then spread it farther, much as in regular neural networks. CNNs distinguish themselves by expressly assuming input to be pictures. They are specifically utilized for the analysis of picture data because of this. Regular neural networks do not scale well to entire visuals. In lower dimensions, they can be controlled, but as the dimensions grow, more neurons and parameters are required, which leads to overfitting becoming problematic. The system is trained using the CNN model, which consists of four layers: an input layer, a convolution layer, a global max pool layer, and a fully connected layer. Sentences or documents formatted as a matrix serve as CNN's inputs. Every row in the matrix represents a single token, which is usually a word but might also be a character. In other words, a word is represented by a vector in each row. Word2vec and GloVe are examples of word embedding, or low-dimensional representations; however, these vectors can also be one-hot vectors that index the word into a lexicon. Visual recognition tasks are one area in which convolutional neural networks shine. Many well-known computer vision networks, including VGG, LeNet, AlexNet, Inception, and ResNet, are available to you. Image recognition is a typical objective in the building of these neural networks. Multiple neural networks that extract abstract elements from the visual are included in these networks.

This means that during training, these networks require a large amount of memory and computing power. In order to achieve better degrees of accuracy, they also require a more computationally sophisticated network, depending on the number of layers used. AlexNet, for instance, consists of three completely linked layers and five convolution layers. LeNet-5 has seven layers, VGG 16 and VGG 19 have 16 and 19 weight layers, respectively, and GoogleNet (Inception) has 22 layers. These deep networks are difficult to train as they need a lot of memory and processing power [9].

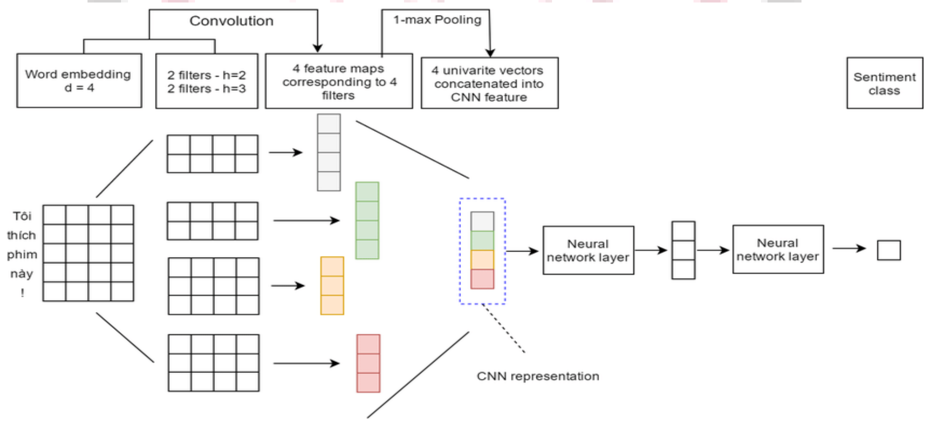

Figure 2: CNN Architecture for Sentiment Analysis [10]

The figure shows CNN architecture for sentiment analysis, in which features are extracted from word embeddings by processing them via convolutional layers with varying filter sizes. To forecast the sentiment class, these characteristics are concatenated and fed through layers of a neural network.

B. DEEP NEURAL NETWORKS

In the realm of textual sentiment analysis, (DNNs) have demonstrated impressive performance in recent times. A subset of machine learning methods known as "deep learning" is part of a wider family of methods that use artificial neural networks and multiple-layer networks to learn tasks. The accuracy of classification is higher for DNN-based approaches than for conventional feature-based machine learning techniques. Recent DNN-based learning methods investigate the combinations of LSTM, BiLSTM, and dual-channel CNN to improve text sentiment categorization [11].

Textual and visual sentiment analyses are both done using DNN. Neural networks employ many layers: an image is delivered to the input layer, where it is processed, and then it is transferred to the output layer to form an output. Because it can process an input picture further, a neural network with several hidden layers sandwiched between the input and output layers is referred to as a deep neural network. A computer can only interpret a picture as a matrix, where each pixel is associated with a value known as activation. Since every neuron is linked to every other neuron, activating one layer simply controls activating the next. The objective is to connect or link the image's pixels to edges, edges to subpatterns, and subsequently include the identified patterns into the picture to assess feelings inside the image. Sentiment analysis of photographs and other visual material is made possible by the development of deep coupled adjective and noun neural networks. Their main objective is to reduce the inter-class variation, therefore they start by investigating deep neural networks for middle-level sentiment representation. The system is then trained utilising networks and learned adjectives under mutual supervision using the Rectified Kullback-Leibler loss (ReKL). Ultimately, optimisation is used to carry out prediction. ReKN is used to train an efficient sentiment representation and remove illogical results. For sentiment analysis of visual pictures, Deep Coupled Adjectives and Noun Neural Networks, or DCAN, are employed. The newly constructed system can provide results for Twitter and SentiBank datasets by analysing the properties of online noisy photographs with the aid of ANP [12].

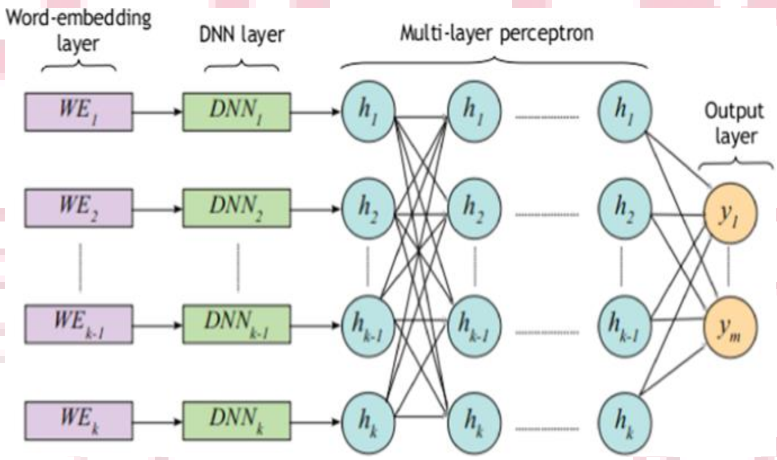

Figure 3: Sentiment Architecture with Deep Neural Networks [13]

The diagram shows a neural network architecture in which each word's embedding are processed by a different deep neural network (DNN) layer. The final output layer is created by combining the outputs of a multi-layer perceptron (MLP) to create a number of output nodes that each reflects a distinct class or prediction.

IV. COMPARATIVE ANALYSIS OF CNN AND DNN MODELS

Table 1 presents a summary of research on neural network-based sentiment analysis conducted between 2013 and 2016. Convolutional neural networks and deep neural networks were used in studies by different academics to analyze sentiment in a variety of datasets, including movie reviews, microblog comments, and photos from Twitter. Key findings include significant performance improvements with models like GoogleNet over AlexNet, top rankings in sentiment tasks, and enhanced accuracy in emotional orientation and sentiment classification. Overall, the studies demonstrate advancements in neural network applications for sentiment analysis across different data types and research objectives during this period.

Table 1: Comparative Analysis of Sentiment Analysis Studies Using Neural Networks [14]

Model Used	**Purpose**	**Data Set**	**Results**
Convolutional Neural Networks (CNN)	Visual Sentiment Analysis (SA)	1269 images from Twitter	GoogleNet gave almost 9% performance progress than AlexNet.
	Micro-Blog Sentiment Analysis (SA)	1000 microblog comments (HuaQiangu)	Effectively improved the accuracy of emotional orientation.
	Textual-visual Sentiment Analysis (SA)	Getty Images, 101 keywords	Joint visual and textual model outperforms the early single fusions.
	Sentiments of sentences	rottentomatoes.com (contains movie review excerpts)	The proposed model outperformed previous models with 45.5% accuracy.
	Phrase level and message level task SA	Semeval-2015	Ranked 1st in phrase level subtask and 2nd in message level task.
Deep Neural Network (DNN)	Visual and Textual Sentiment Analysis (SA)	Sanders Corpus, Sentiment140, SemEval-2013, SentiBank Twitter Dataset	CBOW-DA-LR model obtained superior classification accuracy than previous models.
	Document Similarity Estimation	T&C News	The proposed method accomplished superior performance in terms of similarity estimation.

V. CONCLUSION

In conclusion, demonetization in India illustrates the complexities of economic policy implementation and its societal ramifications. While intended to combat corruption and illegal financial activities, demonetization's economic disruption and adverse effects on marginalized communities were significant. Through sentiment analysis using neural networks, this study showcased the diverse range of public opinions and emotional responses captured from Twitter data. CNNs and DNNs proved effective in analyzing sentiment from textual and visual inputs, offering valuable insights into public sentiment dynamics during a major policy event. Despite its challenges, demonetization raised awareness about financial transparency and accountability, underscoring the evolving role of social media in shaping public opinion and policy discourse. Future research could further explore sentiment analysis methodologies to enhance understanding of public reactions to economic policies in real-time through social media platforms like Twitter.

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