Geospatial Data Analytics- A Deep Learning Perspective

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***Abstract*— To visualize high-dimensional geospatial data has achieved much importance in last decades. But to analyze it, the technologies used of machine learning are not so convincing and thus it is high time to switch to a sub-domain of machine learning called deep learning, which has gained popularity because of its accuracy in processing and analyzing high-dimensional data. The convergence of deep learning with geospatial data analytics shall prove to be a boon to those who actually has a need to predict specific outputs over geospatial data. In this paper, we have presented some geospatial data generated using the GIS (Geographic Information Systems) technology and proposed ways to implement deep learning over these data. GIS technology is a mapping technology which signifies high-dimensional geospatial data and our aim is to propose a model where GIS converges with highly efficient deep neural networks such as CNN (Convolutional Neural Network), RNN (Recurrent Neural Network) and LSTM (Long Short-Term Memory Network). We have provided geospatial as well as statistical results in this paper to visualize practically the GIS technology. This paper further provides future scope of the proposed model which shall present the challenges that needs to be tackled in future and its applicability in many relevant domains.**

Keywords*— Geographic Information Systems (GIS); Deep Neural Networks; Convolutional Neural Networks (CNN); Recurrent Neural Network (RNN); Long Short-Term Memory Network (LSTM); Raster Data; Vector Data.

I. Introduction

Recent years have experienced the rage of deep learning which is a sub-field of machine learning well-known for the accuracy it provides in tasks of object detection, feature extraction and many more. Deep learning has proven its proficiency in multiple domains such as computer vision, natural language processing, speech recognition are a few areas to mention [1]. GIS technology needs deep learning in order to classify spatial, spectral as well as temporal data from high-dimensional hyperspectral datasets. The usage of hyperspectral images in the domains of mineral detection, urban mapping, environmental management, and many such is indispensable [2]. The advent of GIS technology has led towards the research direction in which deep learning acts as a backend technology for providing predictive power to GIS. Effective feature selection using deep learning in the GIS datasets leads to high-ended performance as well as accuracy in prediction [3]. Last decade led to the advent of a research area for image classification which can solve the problem of classifying satellite imagery [4]. The use of machine learning is outperformed in many domains of computer science by the deep neural networks. The reason being the problem faced in machine learning in order to achieve high accuracy in classifying many unsolved categories. Furthermore, deep neural networks came into existence to solve the challenges faced by machine learning in a proficient manner. The data files called geo-data in case of GIS technology consists many attributes along with east coordinates and north coordinates which make it geospatial. Many applications in the domain of GIS which require deep learning as the key enabler for prediction mechanisms are in action. Few of them are as follows:

Estimation of building Energy Use Intensity (EUI) using a GIS based data mining approach proposed by Ma and Cheng [5]. Vector type map generation from aerial imagery datasets using deep neural networks proposed by Sahu and Ohri [6]. Crime prediction is also a field where deep learning and GIS merger can prove its efficiency since till date crime detection mechanisms have been shown still no real-life use cases are available for crime prediction [7, 8, 9, 10]. The applicability of deep learning in context to GIS is large and vivid and we have mentioned only a few.

A. Motivations

This is high-time where GIS technology must meet the competencies of deep learning. GIS technology deals with geographical data and the advent of spatial data mining led us to the idea of converging deep neural networks with geospatial hyperspectral datasets.

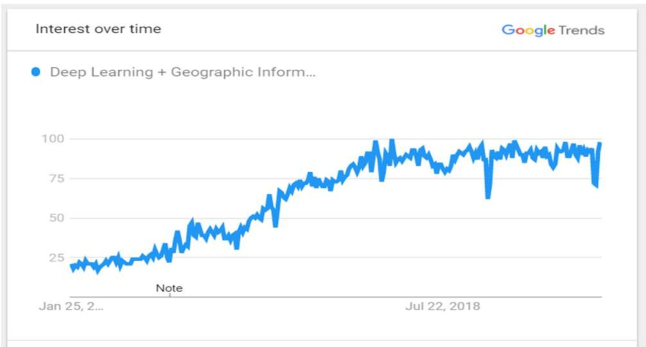

Fig. 1. Google Trends data for the research over five years in deep learning and GIS merger.

Fig. 1 presents the Google Trends data showing the increasing rage of deep learning in the field of geographic information systems over the past five years in a worldwide basis [11].

B. *Objectives*

The objectives of this paper can be summarized as follows:

- Exploring the applicability of deep learning in the field of GIS technology.
- Providing a generalized framework over which any GIS application can use deep learning if required.
- Providing future research directions for the merger technology of deep learning and GIS.
- Citing specified applications as case studies for visualizing the practical competency of the merger technology.
- Detailing of the key enablers to realize such a proposed model.

II. ENABLING TECHNOLOGIES

A. *Geographic Information Systems (GIS)*

GIS may be defined as a special-purpose database where the data points are spatial coordinates. GIS databases work with the aid of geo-references for the storage and retrieval of geo-spatial information [12]. Geospatial data may be considered a high-dimensional hyperspectral data which can be visualized as a map. The data file is integrated with latitude and longitude coordinates which makes it a geospatial data and it acts as an input for the GIS tool which performs geospatial information mining. Furthermore, GIS technology has proven its proficiency in the field of cartography. The data formats range from raster data (grids of pixels) to vector data (polygons defined over pixels). The applicability of GIS technology is an ever-increasing domain of research. Fig. 2 represents the visualization of GIS technology using Google Earth. The considerations of layers which we added over the map were Borders and Labels, Places, Roads, Buildings, Oceans, Weather acting as features in the map.

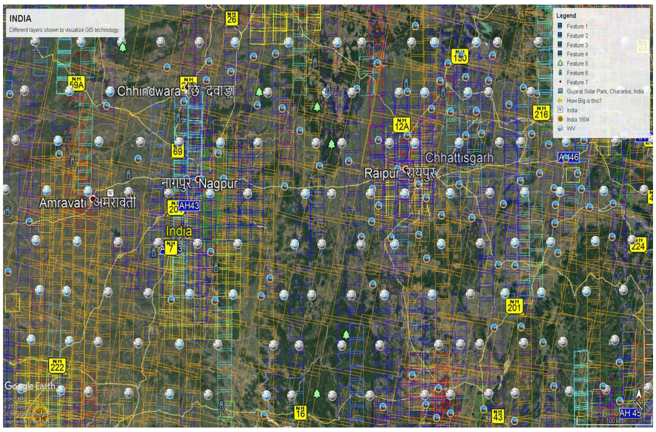

Fig. 2. Practical Visualization of GIS maps with various layers using Google Earth.

B. *Deep Learning in context to GIS*

The applicability of deep learning in GIS technology is indispensable. Many advancements in recent days have been witnessed showing the vast area of GIS where deep learning has proven its proficiency. In context to GIS, road accident prediction, crime hotspot detection, satellite imagery analytics are a few to mention. The spatio-temporal datasets can be analyzed using some machine learning techniques which can never be neglected but the stages of Image Classification, Object Detection, Semantic Segmentation and Feature Extraction can be well-performed and realized only through deep neural networks such as CNN (Convolutional Neural Networks). The temporal features can be analyzed using RNN (Recurrent Neural Networks) as well as LSTM (Long Short-Term Memory Network) based on type of application. The rage of deep learning has nearly outperformed multiple usages of machine learning still some domains like GIS technology still needs further exploration.

C. *Deep Neural Networks*

The deep neural networks are simply the impersonation of human brains with accuracy providing feature based on number of hidden layers in use. The more the number of hidden layers, the more is the accuracy. The deep neural networks constrained to the domain of GIS technology are as such:

CNN: Convolutional Neural Networks are well-known for the features it provides in object detection as well as feature extraction from high-dimensional imagery datasets. The input imagery data is passed through maximum pooling which is further passed to the fully connected layers in order to practically visualize the image classification feature, it is well-known for. In context to GIS technology, geo-datasets consist mapping information, satellite imagery, images from surveillance cameras and many more such imagery data which needs analysis and thus CNN can be used for object detection and feature extraction since its proficiency is well-proven.

RNN: Geospatial datasets consist many information other than mapping information like latitude and longitude instances. To work over those data, we need to use RNN as we can't work on temporal data using CNNs. Temporal data signifies the time-based data which are actually indispensable and must be shown over the plotted data points to instantiate what actually the data point specifies.

LSTM: Long Short-Term Memory Networks are a modification of RNNs with feedback connections among the neurons. The network consists of a forget gate and so is the name short-term memory. This network in context to GIS is used to classify and process the temporal instances of the spatio-temporal datasets.

III. RELATED WORKS

After a lot of filtering, we have selected five recent and relevant papers which shows the increasing popularity and applicability of the merger of deep learning and GIS technology in multiple domains.

Li et al. [13] proposed a model to assess land prices of Shenzhen, an urban city in China. The model considered natural, socio-economic and market factors as prime attributes to assess land prices. This article used the GIS technology for mapping the land under consideration and implemented deep learning over it to assess the above-mentioned factors which affects the land price. In other words, the article explored the land price evaluation methodology using deep hybrid neural networks with spatial data analysing competency. The proposed model first distinguished spatial and temporal factors and then used multi-layer convolution mapping as well as multi-layer RBM mapping to combine it to a deep hybrid neural network. Furthermore, the network was trained and demonstration test performed. Finally, the results were compared with GWR and Hedonic models.

Chen et al. [14] introduced classification of hyperspectral data using deep learning. The article tried to gain the highest accuracy of classification results over hyperspectral data by converging deep learning, logistic regression and principal component analysis (PCA). Furthermore, this paper used stacked autoencoders for high-dimensional feature extraction. The considered datasets were NASA's KSC dataset and Pavia dataset which are geospatial data exposed to SAE-LR, which is the proposed methodology to classify the hyperspectral data. Furthermore, the experimental results presented the proposed model as a competing method towards classifying the high-dimensional hyperspectral datasets.

Audebert et al. [15] explored significant use cases and valid deep neural networks for performing semantic labelling of satellite imagery. This paper used the proficiency of convolutional neural networks for multispectral imagery data. Furthermore, this article focussed on proving the accuracy achieved on using deep neural networks over OpenStreet Maps. The considered datasets were DFC 2017 and ISPRS Postdam. The proposed method involved coarse-to-fine segmentation over highly structured semantic data for exposure to deep neural networks. Also, the method used dual-stream convolutional neural networks to perform test after the merging of optical and OSM data with the aid of FuseNet architecture [16].

Campbell et al. [17] focussed on the use of deep learning in the detection process of traffic signs acquired from Google Street View imagery. Furthermore, the paper aimed at the use of object detection which is best done through deep learning over a dataset economically created using Google Street View imagery data. After training the proposed model to classify traffic signs, with the aid of photogrammetry, the article plotted the calculated location values over a 2-D plane. Furthermore, the plotted classified instances were implemented as an asset management system. The achieved detection accuracy with the use of a merger of deep learning, GIS technology and Google Street View API was 95.63% and the achieved classification accuracy was 97.82%. This showed the applicability of deep learning over GIS proven to be the best as compared to many other algorithms used for prediction as well as detection.

Zhao et al. [18] proposed a novel framework acronymed SSFC which refers to Spectral-Spatial Feature-based Classification. The technology used for spectral feature extraction was dimensionality reduction and for spatial feature extraction was the best-known deep learning. The algorithm proposed for the extraction of spectral features from a hyperspectral dataset was a balanced local discriminant embedding algorithm acronymed BLDE. Furthermore, the paper used convolutional neural networks (CNNs) for spatial feature extraction from high-dimensional hyperspectral data. Finally, the spectral as well as spatial feature were made to work in fusion to achieve a multiple-feature-based-classifier which was trained with HSI imagery datasets and experiments accordingly were performed to prove the novel framework, the best one.

IV. PROPOSED MODEL

The proposed model signifies the merger of deep learning with GIS technology and provides an overview of the working of such a merger technology. The model is a 4-layered model where each layer is an overview of what the work it performs. The first layer is the input layer which signifies the types of input that can be received in such a framework. The input layer formats are classified further into raster formats which signify grids of pixels, vector formats referring to polygons or lines or curves defined over pixels acting as points. Furthermore, pre-built maps can also act as an input for this framework. The input layer data is next passed to the second layer of geospatial data processing where the processing and visualization of the input data is done with the aid of GIS tools such as ArcGIS, QGIS, Maptitude and many more. Furthermore, the Python libraries like GeoPandas, ArcPy, PyGRASS can also be used for the concerned data processing. Many web-based tools for mapping and visualization can also be used. The processed data can next be exposed to the third layer which converges deep learning over the GIS maps which is succeeded by object detection and pixel classification. The deep neural networks are used based on the type of input they receive. We can't think of prediction or detection over spatial data without having any temporal instances. Thus, to work over temporal instances, RNN and LSTM networks can be of utmost importance but for working with spatial data CNN is proved to be the best. Finally, the GIS maps merged with predictive power is produced as output.

The task of geospatial data processing is the most important task and can be done by plotting the required data points over a map of interest which can be done using many current day tools like ESRI's ArcGIS, GeoPandas by Python, CartoPy by Python, QGIS, Maptitude and many more. These tools are used to plot data points based on geospatial datasets which consist the latitude and longitude information along with the required classifiable features.

The spatial data needs to be classified and analysed by passing it through the convolutional neural networks which further shall be capable of any object detection activity or pixel classification competency with feature extraction working as the main feature. Furthermore, the temporal data can be exposed to recurrent neural networks or long short-term memory networks based on the application type. The data points thus obtained after the prediction task is over is thus plotted over the corresponding map which can be obtained through tools like Google Earth and many such. The map obtained as the output shall further consist of information that are relevant to a particular geographic location.

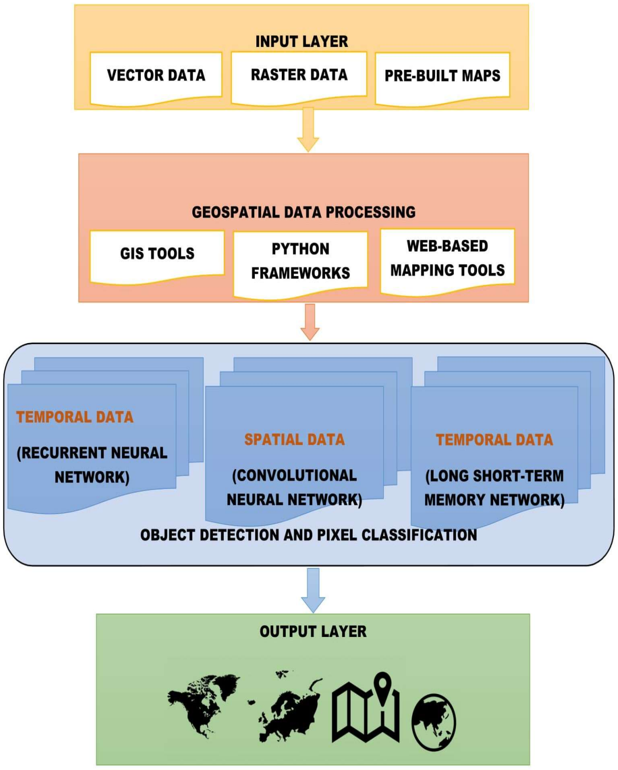

Fig. 3. Proposed framework for the convergence of Deep Learning with GIS technology.

V. EXPERIMENTAL SETUP AND RESULTS

We have performed experimentation to visualize the second layer of the proposed model. The main objective is to provide a research flow towards the necessity to use the deep learning frameworks in convergence to GIS technology. The experiments performed used QGIS software package to visualize the considered dataset.

A. *Dataset Specification*

We have considered the Indian census dataset [19] for the purpose of visualizing the GIS technology. The dataset consists of Indian population data from 2001 to 2011 with geospatial indices which makes it suitable for use in this research article.

B. *Results and Discussions*

The district wise population in the year 2001 and 2011 can be visualized as such:

The visualization of the map with districts as labels provided as the basic overlay is shown in Fig. 4. Furthermore, the point-cluster analysis, heatmap analysis and K-means clustering is shown in Fig. 5, Fig. 6 and Fig. 7 respectively. The K-means clustering is performed with 5 clusters represented in Fig. 7. The kernel density estimation is used to present a heatmap which is shown in Fig. 8. The raster histogram for the corresponding heatmap generated by using kernel density estimation is shown in Fig. 9 where for a single-band of color we have generated the frequency histogram. The bar-plot for state wise population in 2001 is shown in Fig. 10. The box-plot for state versus population in 2011 with mean and standard deviation embedded within the plot is shown in Fig. 11. The 2-dimensional scatterplot comparing the populations in 2001 and 2011 is shown in Fig. 12. The Pareto plot, Clustered column chart and the bubble chart for varying attributes are shown in Fig. 13, Fig. 14 and Fig. 15 respectively.

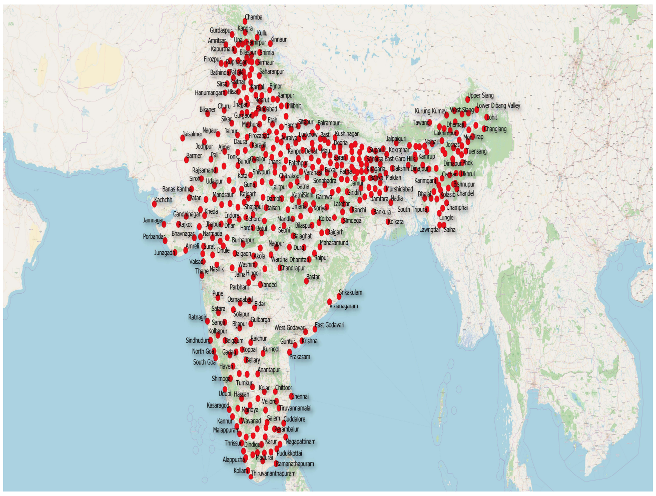

Fig. 4. Overlay analysis of the Indian census dataset with district names as labels.

Fig. 5. Point Clusters generated for the dataset shown as yellow symbols.

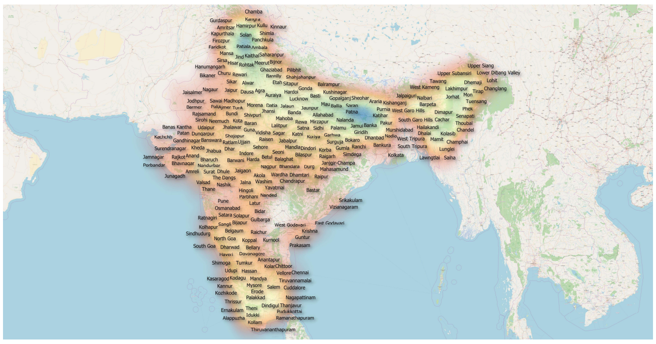

Fig. 6. Heatmap Generated showing higher populated regions in dark colour.

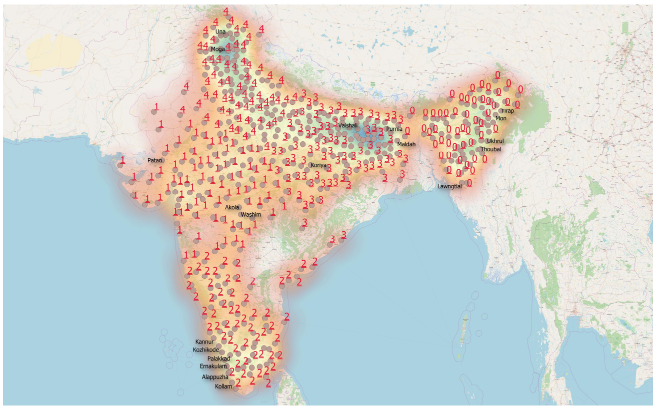

Fig. 7. K-means clustering performed with 5 clusters shown in underlines as 0,1,2,3,4 over the heatmap generated for the dataset.

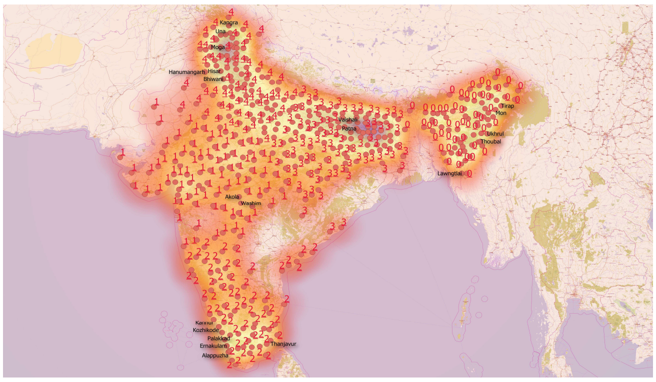

Fig. 8. Kernel Density Estimation performed to show the heatmap for the dataset.

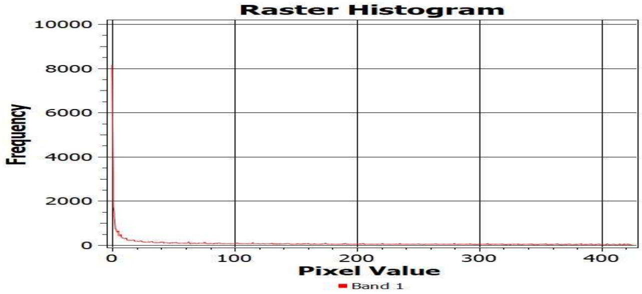

Fig. 9. Corresponding raster histogram for the kernel density estimated heatmap generated.

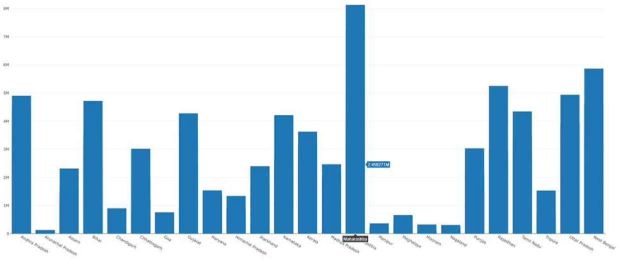

Fig. 10. Bar Plot for state-wise population in 2001 with highest population shown to be in Maharashtra.

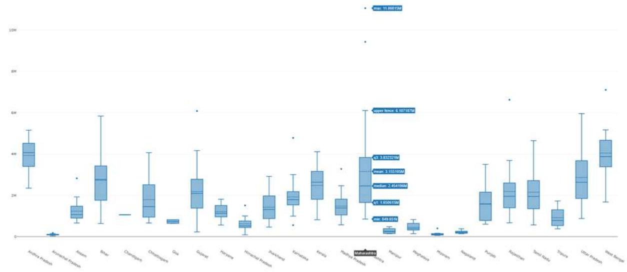

Fig. 11. Box plot with maximum mean and standard deviation shown for population in 2011.

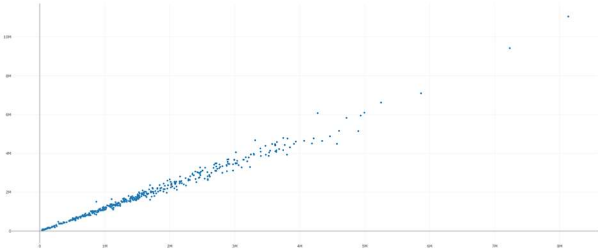

Fig. 12. 2-Dimensional Scatterplot for population in 2001 versus population in 2011.

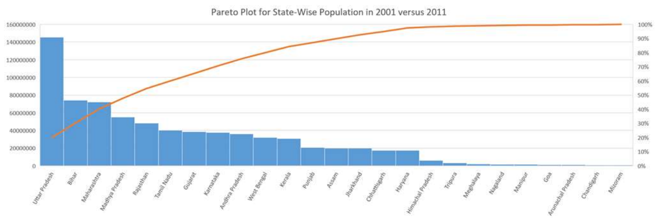

Fig. 13. Pareto Plot showing State versus population for the years 2001 and 2011.

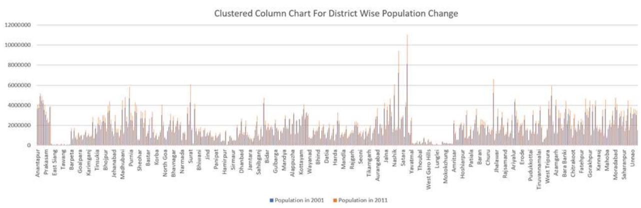

Fig. 14. Clustered Column Chart Generated for District-Wise Change in population.

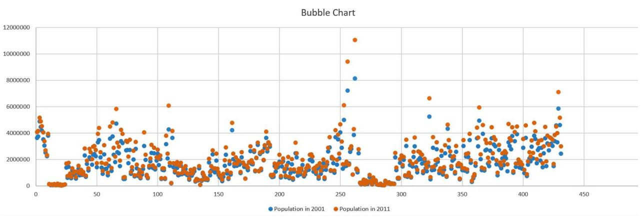

Fig.15. Bubble Chart comparing the populations of 2001 and 2011.

VI. ENABLING TOOLS

There exist many visualization tools but we have generated the overlay map, heatmap, point-cluster map using the QGIS software package. Furthermore, we have used the Processing Toolbox of QGIS for performing K-means clustering and kernel density estimation. The bar-plot, box-plot and scatter-plot is generated with the aid of Graphics menu under the Processing Toolbox of QGIS software package. The Pareto-plot, Clustered Column chart and Bubble chart is generated using Microsoft Excel 2019.

VII. CONCLUDING REMARKS AND FUTURE SCOPE

In this paper, we tried to visualize high-dimensional geospatial data and the proposed framework presents a future research direction towards the use of deep learning in context to GIS technology. The spatial instances can be analyzed and feature-extracted using the CNNs whereas the temporal instances with the aid of RNNs and LSTMs. The present data tools for GIS need much further integration with deep learning for providing much predictive power to GIS with higher accuracies and precisions. This paper with the aid of present-day visualization tools has generated both geospatial as well as statistical results. The task of geospatial data processing needs much more ease further. This unique merger technology can assist in many upcoming application areas of GIS technology. Further research is required in using the deep learning toolkit over such hyperspectral data. Our motive was to present the viewers with the challenges faced when we are using the tools for GIS without the need of deep learning. Thus, with deep learning, the development of GIS applications is shown as a future research direction. The convergence of machine learning with GIS technology has been practically visualized in this paper leaving behind a future research direction in the field of merging the sub-field of machine learning i.e., deep learning with GIS technology for more functionalities.

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