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A Survey and Analysis of Intelligent Forecasting and Decision-Making Evaluation of Urban Growth using Artificial Intelligence

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Abstract: A dense concentration of human-made features such as residences, businesses, highways, bridges, and trains characterize urban areas, which are developed regions that encircle cities and are home to most of the population's non-agricultural labourers. Monitoring and modeling urban development have become critical for long-term urban planning and decision-making. Urban growth prediction models are crucial for understanding the causes and implications of urban land use patterns and predicting upcoming growth of city based on the current scenario, ensuring sustainable city development. The Cellular Automata (CA) approach has been used to simulate the urban growth in a hypothetical region, based on principles governing cell spatial interaction and parameters for exploring alternative urban shapes. However, CA faces numerous uncertainties and more research is requited to enhance its adaptability to urban environments. In recent times, Artificial Intelligence models like Machine Learning (ML) and Deep Learning (DL) are being utilized for urban growth prediction, enhancing decision-making and overcoming uncertainty. In order to help with future urban development planning, these models are essential for accurate management and control of urban expansion. This article presents a comprehensive review of ML and DL models for urban prediction. The first step is a quick review of the many urban prediction models developed by various academics using ML and DL models. The next step is to provide a new way for reliably projecting where cities will expand in the future by comparing current frameworks and determining their shortcomings.

Keywords: Urban Area, Cellular Automata, Machine Learning, Deep Learning, Decision Making

I. INTRODUCTION

An urban area is a geographical location that is characterized by continuous urban habitation. It has a larger population density than the surrounding space, albeit the values of the density vary greatly among nations and depending on the kind of urbanization [1]. A centre component of an urban region consists of a more or less big metropolis or town and surrounding suburbs which were formerly separate but have since been absorbed via agglomeration processes [2]. The rapid growth and shape of urban developments are gaining interest along with the linkages between cities and rural areas, influenced by economies, societies, cultures, and the environment [3].

Urbanization is a phenomena inherent in human civilization that represents itself in numerous ways throughout history. Cities have grown swiftly as a consequence of population increase and economic development [4]. It is critical for current and future civilizations that urban expansion proceeds in the most efficient manner possible, maximizing advantages for urban populations while reducing both economic and environmental costs. Over the last two decades, urban development studies have received a lot of attention, particularly since metropolitan areas are continually and quickly increasing all over the globe [5]. The work of controlling urban expansion has grown in both breadth and complexity, and it is regarded as one of the most critical tasks of the twenty-first century. The prediction of urban growth is critical for analysing potential environmental changes, identifying pre-expansion patterns and understanding urban sprawl behavior in order to effectively plan infrastructure and manage resources in urban areas, thereby improving environmental planning and resource management [6]. As a result, forecasting a city's future population growth is essential.

Recent developments in the availability of GIS-based modelling tools and high-resolution temporal satellite data have improved the processing and analysis of spatial data, leading to more accurate predictions of urban expansion [7]. Synoptic views, repeating coverage, and real-time data collecting are all features of the urban growth prediction model, which employs satellite remote sensing data to track land-use change with high temporal resolution. In order to keep the spatial data infrastructure running smoothly for future estimates of urban growth, this digital data precisely calculates Land Use and Land Cover (LULC) categories [8]. But, the system was unable to detect and differentiate specific physical properties without the addition of additional non-visible bands. GIS is a crucial tool in urban growth prediction, guiding planners in the development of settlements and infrastructure facilities. It provides urban planners with enhanced data visibility, enabling them to monitor fluctuations, evaluate project feasibility, and predict environmental impacts over time [9]. However, it shows spatial relationships but does not provide absolute solutions and acquired high memory space.

In developing nations in particular, CA models are utilized extensively for the purpose of forecasting and assessing urban transformation [10]. These models improve our knowledge of city dynamics by mimicking urbanization and the intricate relationship between land-use changes and city sustainability. Image pixels, states, neighbourhoods, and transition rules are all part of CA's set of parameters and guidelines for investigating urban forms [11]. It works well for modelling complicated geographical processes such as population expansion, land use change, and urbanization. Prior to making decisions regarding the development of urban areas, CA aids governments, planners, and stakeholders in predicting and evaluating possible policy outcomes [12]. However, CA faces numerous uncertainties and more research is requited to enhance its adaptability to urban environments. Also, this model fails to account for spatial heterogeneity changes indicating a potential for over- or under-simulation in urban growth prediction systems.

Figure 1 Satellite Images of Urban Area

Figure 2 GIS in Urban Area

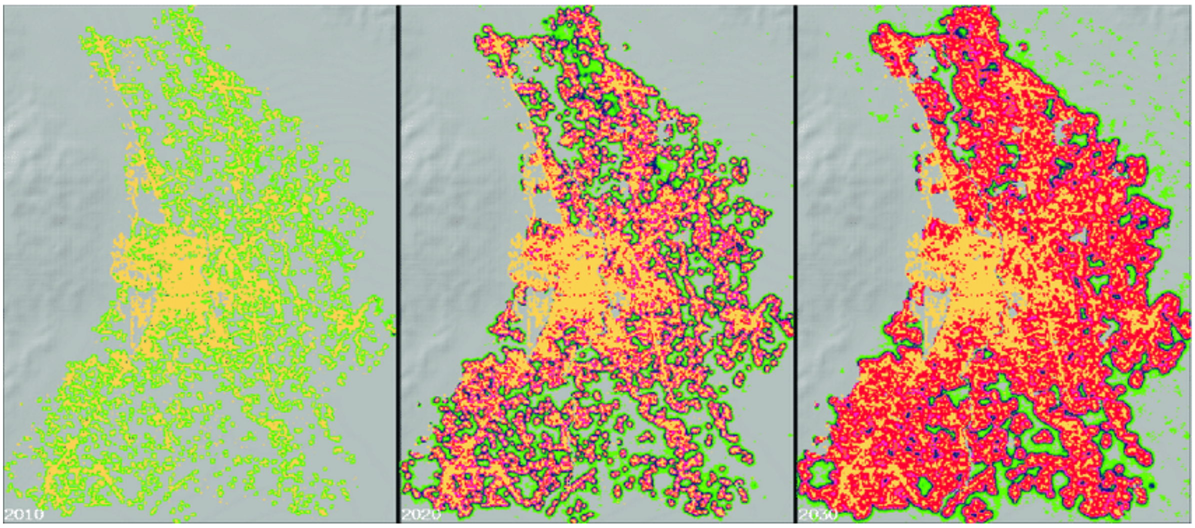

Figure 3 Sample CA model for mapping urban growth and dynamics. The left side depicts the urbanized area in 2010, the centre image shows the 2020 urbanized projection and final one id for 2030 urban projections [13]

In present, Artificial Intelligence (AI) have extended the possibility to utilize in the prediction of urban growth, enabling sustainable natural resource planning for better economic yield in urban area development [14]. AI incorporates ML and DL models, which have a greater influence on technical advancements in this conservation disciplines to enhance prediction rates. Policymakers and urban planners can gain a better grasp of the spatial ambiguity and temporally randomness associated with future urban growth with the help of these models [15]. ML models are hypothesized with efficient data interpretation, précised decision making, provides sustainable management of urban centers for future planning [16]. ML algorithms include Support Vector Machines (SVMs), Genetic Algorithm (GA), K-Nearest Neighbour (KNN) Random Forest (RF), Navies Bayes (NB) Artificial Neural Networks (ANNs), Decision Tree (DT), Bayesian Networks (BNs) and so on. These algorithms aims to identify the data correlations from the complex patterns, benefits to provide automated tasks for developing new hypothesis on predicting the urban growth level in the cities [17]. However, ML based urban prediction models face a significant challenge in generalizing beyond their trained data which can lead to inaccurate predictions when presented with significantly different data from the training data.

Deep learning (DL) models are a subset of machine learning (ML) models that are practical, end-to-end, and capable of automatically learning representations of features from raw data and subsequently producing outputs [18]. DL applications create models that simulate indicators from city shape input elements, requiring mastery of associated indicators for urban growth monitoring. These models help to understand urban growth dynamics, crucial for urban planning and policy decision-making for urban and regional policy planners [19]. DL have proven its capacity to capture complex spatiotemporal phenomena for the urban growth modelling. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long-Short Time Memory (LSTM), Deep Belief Networks (DBN) and so on. These models aid in automated prediction and decision-making using vast data provided by the urban planners to estimate population, commodities and land usage for future urban growth area planning and development [20].

To forecast city expansion, ML and DL models examine supplementary geographic data, grid-based soil details, meteorological monitoring data, LULC data and rivers. These models significantly impact city operations and planning due to the increasing generation of data, which urban planners will use to analyze, predict, and understand urban dynamics, enhancing their ability to detect patterns [21]. A wide range of articles in the literature using ML and DL methods have yielded to provide promising solutions for improving urban growth prediction, optimizing city planning, and benefiting the public good. This paper's primary objective is to survey the state of the art in urban growth detection using ML and DL-based solutions in order to better understand and anticipate urban dynamics in the future. Also included is a comparative study that discusses the pros and cons of those frameworks in order to point to potential future directions.

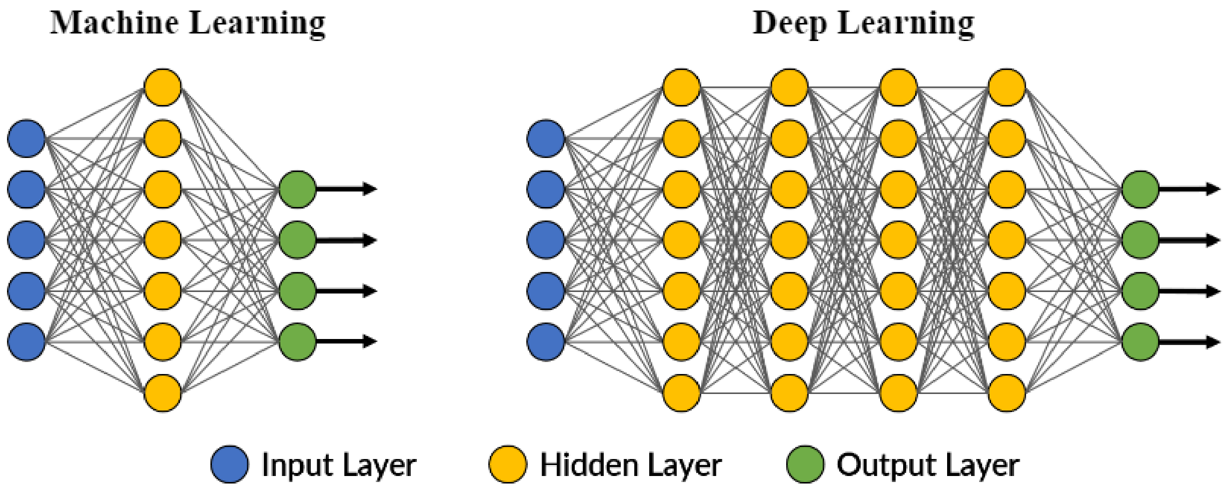

Figure 4 Structure of ML and DL

Here is how the remaining sections are prepared: Several ML and DL-based frameworks for detecting urbanization are covered in Section II. A comparison of those frameworks is presented in Section III. Section IV provides a synopsis of the full survey as well as suggestions for the forthcoming scope.

II. SURVEY ON URBAN GROWTH DEVELOPMENT USING ML AND DL MODELS

In order to forecast city expansion, Aarthi and Gnanappazham [22] built a CA model using agents-based Neural Network (NN) coupling. The land cover features, including built-up, vegetated, waterbody, and open land, were then classified using a SVM model. The next step was to merge several land cover types into one, and then sort the resulting maps into Built-up and Non-Built-up categories. To model the hotspot sites utilizing government policy for urban growth forecast, prediction models such as Traditional CA (TCA) model, Agents based CA (ACA) model, and NN coupled Agents-based CA (NNACA) model were employed.

Mu et al. [23] suggested Self-Adaptive Cellular based DL (SACDL) with multi-sourced data change prediction in LULC for urban growth identification. In this method, various input data sources including remote sensing, economic, weather, and construction data to improve prediction accuracy. A self-adaptive cellular method normalizes and formalizes this data, which can be directly fed into LSTM model which was utilized for LULC prediction due to its superior long-term series processing ability to evaluate the urban growth modelling and prediction.

Gómez et al. [24] constructed a spatiotemporal modeling of urban growth using ML framework. The collected satellite images was pre-processed, normalized to remove clouds and no data values. In order to determine the distribution of the population, the binary urban footprint, and the colored urban footprint, the acquired images were subjected to the content-aware spatial resampling (CASR) method. By adding together the population numbers of every pixel in the picture, Temporal Interpolation was utilized to determine the overall estimated population. In order to estimate future urban expansion, the Spatio-Temporal Regression (STR) Model was employed to forecast population distribution.

In order to track and foretell how cities will expand in the future, Mostafa et al. [25] built an ML model that makes use of satellite imagery. After getting LULC maps from Landsat photos, the ML model picks the right variables, makes maps of likely transitions, checks its own correctness, and makes sure that changes are detected. The LR algorithm and Markov chain model were utilized in the Land Change Modeler (LCM) for the purpose of simulation and future prediction. To examine the relationship between changes in various land-use types, LR analysis was employed. When satellite pictures are unavailable, a multi-criteria decision-making technique called Fuzzy-TOPSIS is used to identify which districts are most at danger from urbanization.

In order o identify changes in cities using aerial photos, Fyleris et al. [26] proposed a DL model. Extracting features and classifying them initially involved using a pre-trained DeepLabv3 model with a ResNet50 backbone that had been trained on ImageNet data. There were two stages to the model tweaking process. To begin, an autogenerated coarse dataset was used to adjust the Open Street Map OSM data. Then, during the fine-tuning stage of the urban change detection job, the final adjustment for each period was established using the revised data.

To enhance the forecast of urban expansion through the automated generation of transition rules, Ghobadiha & Motieyan [27] proposed an Adaptive Network-based Fuzzy Inference System (ANFIS). This approach used ANFIS in conjunction with several input division methods, such as ANFIS with grid partitioning (ANFIS-GP), subtractive clustering (ANFIS-SC), and fuzzy c-means clustering (ANFIS-FCM). After that, the CA-MC approach was created to test how well the urban growth prediction worked with real-world data. In order to forecast and classify LULC changes for the purpose of urban growth planning,

Jagannathan and Divya [28] introduced an HGVGG19 approach. Using the training data transferred from the RestNet50 method, the HGVGG19 method was developed using the hybrid hot encoding VGG19 method. The process began with the collection and feature-based classification of satellite and aerial pictures from multiple sources. Before training the HGVGG19 model, the image dataset underwent pre-processing utilizing an image augmentation technique, which involved resizing and processing the images. In the end, the HGVGG19 approach was employed to forecast LULC changes in order to model urban expansion.

In order to evaluate city expansion and feasibility, Khan et al. [29] built an ML model. In order to predict and prepare for future urbanization based on satellite imagery, this model employed an Artificial Neural Network - CA (ANN-CA). In these photos, the Land Use\Land Cover Monitoring (LULC) maps were used to assess the development of the urban expansion. To better urban planning growth and prevent further urban sprawls, the model was verified using a confusion matrix, geographic similarity, Kappa statistics, and Root Mean Square Error (RMSE).

The spatio-temporal aspects of urbanization were modeled using a machine learning model developed by Kim et al. [30]. Using historical data on both internal and external changes, this model used Logistic Regression (LR) to categorize areas as either having low or high urban growth. By distributing funds and guiding resources properly for local policymakers, this model allows for precise predictions of urban growth independent of external variables. To improve the accuracy of urban growth forecasts, it makes use of the leading non-linear connection derived from historical data on urban developments in each location and its surrounding areas. In order to detect urban growth, Kim et al. [31] built a Convolutional Long Short Term Memory (Conv-LSTM) model. This approach used Conv-LSTM to forecast the urbanized land by analyzing nearby characteristics at the local scale. To take independent variables influencing urban expansion over longer time periods into account, Multi-input ConvLSTM was set up and used to make predictions.

An Urban Change Detection Network (UCDNet) was developed by Basavaraju et al. [32] using Sentinel-2 bi-temporal multispectral satellite images. This method employed an encoder-decoder design that relied on Modified Residual Connections (MRC) and the New Spatial Pyramid Pooling (NSPP) block, which enhances prediction accuracy by monitoring the shape of dynamic regions. While the NSPP block provides information about the global context through the extraction of multi-scale features, the MRC helps with the adaptive localization of changes. When it comes to evaluating urban change prediction, UCDNet uses a loss function that blends WCCE and modified Kappa loss.

In order to enhance urban policy, Mustak et al. [33] proposed a multi-scenario approach to modelling and predicting urban expansion utilizing information from earth observation. To simulate the expansion of cities, researchers used ANN-MLP-Markov and CA-Markov, two types of Artificial Neural Networks. In order to better prepare for future urban growth, we used hybrid geo-simulation models based on machine learning over a number of urban planning factors. For the purpose of detecting urban expansion, Uwizera et al. [34] developed a DL model using satellite imagery. Here, we used t - Stochastic Neighbour Embedding (t-SNE) to transform the similarities between data points into joint probabilities, and then we normalized and pre-processed the resulting satellite pictures. Last but not least, the acquired satellite images had their final features extracted using pre-trained models such as MobileNetV2, Resnet50V2, and InceptionV3. The RF model was used to get the classification label for urban growth prediction from the retrieved photos.

Capital Region Development Authority (CRDA) urbanization was geo-visualized by Bharath et al. [35] using ML and DL models. Datasets in vector and raster formats were first gathered and prepared. To identify non-linearities and get insights from the data, the Random Forest (RF) model was utilized. In the end, the government's rules and regulations were used to forecast urban change using an ANN model.

In order to round out the urban growth simulation in the Min Delta region, Liu et al. [36] built an Ecological Security Pattern-Future Land Use Simulation (EPS-FLUS) model. This model is used to delineate Urban Growth Boundaries (UGBs). The first step was to merge four separate ESPs into a Single Integrated ESP (SIESP) and then to categorize the IESP into three tiers. After that, the WRCC was used to forecast land use demand using a Markov chain. Subsequently, the variables that influenced LULC were chosen using RF. Finally, in order to finish the multi-scenario UGBs delineation, the outputs of the previous processes were combined and input into the FLUS model.

A ML framework was developed by Gharaibeh et al. [37] to evaluate city expansion and conduct appropriateness assessments. In light of impending urbanization, the model seeks to provide land use adjustment and preservation measures. Image analysis, Geographic Information Systems (GIS) and ML were all incorporated into this model. To assess the effects of uniform time intervals on city expansion, a Time Delay Neural Network (TDNN) was proposed. In order to examine the growth and expansion of cities, the ML-based prediction model was combined with land suitability analysis, which incorporates quantitative and qualitative data.

A DL-based Change Detection model was proposed by Srivastava and Ahmed [38] to track the expansion of cities through the use of Sentinel-2 satellite imagery. In order to categorize land cover classes using an ANN and SVM, image indices such as the normalized Difference Built-Up Index (NDBI), Normalized Difference Vegetation Index (NDVI), and Built-Up Index (BUI) were retrieved from the gathered photos. In order to assess the cities, the classified photos were used. Lastly, a DL method was created to track developments in cities that have shifted their focus from agriculture to other sectors in order to analyse potential future expansion.

A DL model was introduced by Zafar et al. [39] to predict how urbanization will affect vegetation and what the future holds. The Enhanced Vegetation Index (EVI), a measure of the future difference between urban and rural vegetation, was predicted using the LSTM-RNN model in this approach. The dataset's variable's mean change over time was estimated using Linear Regression, which assessed the slope. To analyse the relationship between EVI that year and urbanization growth, the Pearson correlation coefficient was used. The purpose of applying LSTM-RNN was to investigate and predict future urban-rural vegetation inequalities in order to promote sustainable urban growth and environmental preservation.

III. COMPARTIVE EVALUATION

In this section, a comparative scrutiny of the above studied ML and DL algorithms for urban growth detection according to their merits, demerits and performance efficiency are illustrated in Table I.

Table I Comparison of ML and DL for urban growth prediction

Ref No.	Methods	Advantages	Disadvantages	Databases	Performance Evaluation
[22]	SVM, TCA, ACA, NNACA	This model concentrated even on small local regions for the growth prediction	High false alarms were observed in the hotspot locations	The data was gathered from academic institutions and IT hubs in the south of Chennai.	Prediction accuracy = 94%
[23]	SACDL, LSTM	The processing efficiency enables the model to deal	High computational time and required large data to train	Satellite images of city Wuhan	Accuracy = 80%

		with real-time data.	the model		
[24]	CASR, STR	Adaptable in real time application to identify the maximum population capacity	High memory space and takes long time to even in smaller regions	GHS Urban Centre Database 2015	F1-Score = 0.83; MSE = $1.712 * 10^{-3}$
[25]	Fuzzy-TOPSIS, LR model, Linear Regression	Lower computational complexity	This model results with uncertainty and overfitting issues	Google Earth historical images	Accuracy = 94.3%; Kappa coefficient = 0.82%;
[26]	Pre-trained DeepLabv3 model and ResNet50	High flexibility and interpretability, lower error rate	Slower convergence rate was resulted	OSM data source	Accuracy = 76.8%; Error rate = 0.176
[27]	ANFIS-GP, ANFIS-SC, ANFIS-FCM and CA-M	Better generalization capability	Long execution time, inability to execute high-dimensional problems and high complexity	Census of the Statistical Iran population Centre	Accuracy = 93.41%; Kappa vales = 0.76
[28]	HGVGG19, RestNet50, VGG-19	Lesser memory space and effective eliminates the overlapping images for the consistent predictions	This model evaluates only for a short period of time	Sentinel-2 satellite images covering Chennai and Coimbatore urban regions	Accuracy = 98.5%;
[29]	ANN-CA	This model enhances urbanization monitoring and planning by implementing appropriate policies and necessary measures.	High computational cost and requires large dataset for training	Multi-temporal LANDSAT satellite data	Estimated accuracy = 82.09%; RMSE = 46.8=50.2
[30]	Logistic Regression	This model works well on large dataset and eliminates the issues of spatial and temporal correlations	This model was only suitable to predicted only for short period of time	Auditor's Parcel Databases are made available statewide by GeoPlan Center. The state of Florida	Accuracy = 92%; RMSE = 34
[31]	Conv-LSTM	Better predictability and flexibility	Restriction zones and army sites were not Considered and more urban spraw methods was required for the future predictions	Ministry of Environment, Korea	Accurcay = 97.5%
[32]	UCDNet, MRC, NSPP, WCCE	High accuracy and eliminates the anchored-size constraints from the network	Prediction efficiency was reduced due to the neglect of key factors such as surplus resources and recreational facilities.	Onera Satellite Change Detection (OSCD) dataset	Kappa factor = 89.58%; Jaccard index (JI) = 81.62% F1-score = 88.99%;
[33]	ANN- MLP-Markov, CA-Markov	Effective decision making and covers the small regional area according to the policies	Highly sensitive to subtle patterns of urban development that occupy a considerable amount of time and space.	Real time satellite images of urban planning areas	Accuracy = 88%; Mean Square Error = 0.79
[34]	RF, MobileNetV 2,	Efficient processing speed to analyze the data	The parameters of these models needs to be fine-tuned to eliminate the	Satellite imagery data retrieved from Google earth 2021	F1-Score = 98%;

	Resnet50V2 and InceptionV3		uncertainty issues		
[35]	RF, ANN	This model works well on large data and reduces the overfitting issues	As the neural network set-up was large, high processing time was resulted	Data collected from Andhra Pradesh regions	Accuracy = 82.54%; Kappa value = 0.914
[36]	RF, Markov chain	Eliminates the noisy-irrelevant data, overfitting issues and also covers the smaller regions for the growth prediction	Loss of information and high memory space	Resource and Environment Science Data Centre (RESD) and National Catalogue Service for Geographic Information (NCSGI) and	Kappa value = 0.785; RMSE = 0.84
[37]	ML TDNN	This model enhances and expand the knowledge on spatial urban growth.	It was trained with limited dataset and lower interpretability was resulted	Statistical Report from Jordan in 2015	Identified region unsuitable for growth = 51%; Moderately suitable = 43%; Highly suitable for growth = 51%
[38]	ANN, SVM, DL	Increased precision and adapts quite well to high-dimensional data	Localization issues and potential over-fitting issues were resulted with this model.	Sentinel-2 images are taken from the Copernicus Open Access Hub Portal	Accuracy = 98.5%;
[39]	Linear Regression, Pearson Correlation coefficient, LSTM-RNN	High generalization ability and provides extended urban sustainability	High processing time and acquired low temporal solutions	MODIS data with total population and population density	Mean Absolute Error (MAE) = 0.31; RMSE = 0.26;

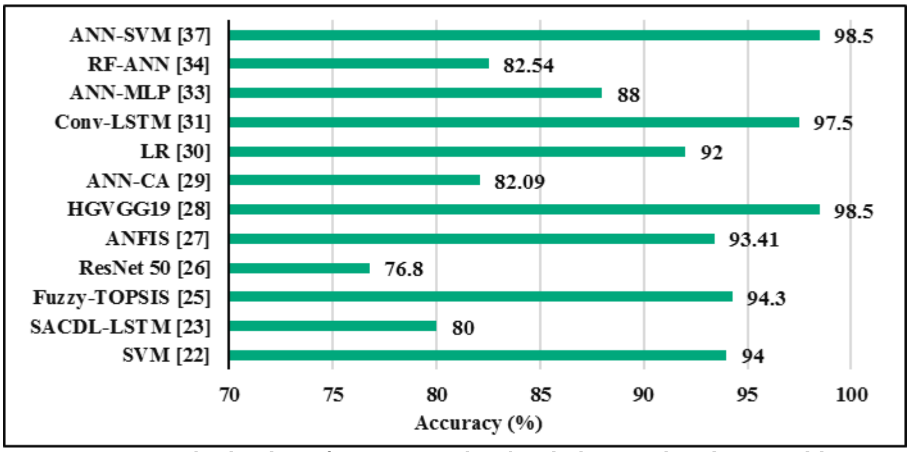

Figure 5 Graphical analysis of various ML and DL based urban growth prediction Models

IV. Performance Evaluation

In this section, the performance evaluation is conducted for the above listed ML and DL based urban growth prediction and classification models in terms of accuracy. The below provided graphical representation in figure 5 indicates the effectiveness of a proposed models in the literature for urban growth forecasting based on population data and future planning in the urban area enhancements and LULC changes predictions.

The preceding Fig.5 shows that the article [28] produces better results for predicting urban expansion and detecting LULC changes using satellite photos. The data used for training in [28] came from pre-processed, enhanced, and scaled aerial and satellite photos. We used the hot encoding VGG19 model to process the categorical data because it couldn't be processed directly. In order to improve the accuracy of urban growth prediction and LULC change detections, it employs the TL method to import training data from the RestNet50 approach. In the above graphical analysis, the article [38] also provides the efficient results for urban growth detection. The article [38] utilized Sentinel-2 satellite images to pre-process, including resampling, re-projection, and computing using different numerical indices. Supervised image classification algorithms like SVM and ANN were applied to predict the urban changed areas, dividing them into positive, negative and no-change areas. Positive changes refer to areas that have become non-urban to urban while no change refers to areas that remain unchanged. Both models offer high accuracy in predicting urban growth in larger cities, enhancing planner productivity in developing future urban areas with less complexities.

V. CONCLUSION

Urban growth is influenced by population growth and citywide planning studies, with horizontal expansion and vertical rise shaping the form of urban growth, with the latter being the primary reason. Traditional urban growth techniques are inefficient, causing urban planners to struggle with future development in urban areas. In recent days, ML and DL models are being utilized to predict urban growth, aiming to maximize population benefits while minimizing economic and environmental costs for present and future societies. This study compared and contrasted various ML and DL approaches to forecasting city expansion, analyzing each one for its own unique set of advantages, disadvantages, and detection efficiencies. Thus, this review aids researchers in selecting efficient urban growth detection methods, enabling better resource utilization, population density evaluation, and informed infrastructure construction decisions for future urban growth areas, ultimately benefiting society in the future. Future research will focus on developing advanced DL models using Internet of Things (IoT) for urban growth prediction, enabling timely intervention and on-spot practices to avoid complications in new urban areas, resulting in improved quality of life and reduced environmental impact.

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