



COMPARATIVE ASSESSMENT OF MACHINE LEARNING ALGORITHMS FOR LAND USE  
AND LAND COVER CLASSIFICATION USING MULTISPECTRAL REMOTE SENSING  
IMAGE

Md Zahid Hasan<sup>1</sup>, Rabeya Sultana Leya<sup>1\*</sup>, Kazi Saiful Islam<sup>1</sup>

<sup>1</sup>Urban and Rural Planning Discipline, Khulna University, Khulna-9208, Bangladesh

KUS: ICSTEM4IR-22/0124

Manuscript submitted: August 18, 2022

Accepted: September 25, 2022

---

**Abstract**

In developing countries, rapid and unregulated population growth, along with economic and industrial growth and development have accelerated the rate of changes in land use and land cover (LULC) during the early twenty-first century. One of the most effective ways to assess and manage the land transformation is through quantitative assessment of LULC changes. To find the best classifier for further uses of earth observation data, it is necessary to compare the accuracy of several LULC modelling algorithms. In this paper, four machine learning (ML) algorithms/classifier namely support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF) and decision tree (DT) have been examined using Landsat 8 Operational Land Imager (OLI) sensor data. All the algorithms performed almost in a similar accuracy level, where SVM scores 84.00% of Cohen kappa and 90.74% of overall accuracy. These figures are 82.99% and 90.05% respectively for KNN. For RF, Cohen kappa and overall accuracy recorded 78.24% and 87.62% respectively. DT gained 74.46% for Cohen kappa and 85.51% for overall accuracy. Clearly SVM outperformed other algorithms in low spatial-resolution satellite data. The outcome of the study would help in different stages of LULC modelling. Moreover, it would help the planners and policy makers in formulation and preparation of land-based policy and planning to ensure sustainable living environment.

**Keywords:** Support Vector Machine, K-nearest Neighbor, Random Forest, Decision Tree

---

**Introduction**

The knowledge of LULC change is crucial in different fields using earth observation data, such field are environmental vulnerability and impact assessment, regional planning, monitoring of natural disasters and hazards and etc. (Talukdar, Singha, Mahato, Praveen, & Rahman, 2020). In order to manage and understand the land transformation the quantitative assessment of LULC dynamics is one of the most efficient methods

---

\*Corresponding author: <rabeya.leya@ku.ac.bd>

DOI: <https://doi.org/10.53808/KUS.2022.ICSTEM4IR.0124-se>

(Mas et al., 2017). LULC change mapping has been recognized as a critical component of wide variety of applications including land use planning and climate change mitigation (Reis, 2008). As a result, assessment of LULC change is required for a variety of purposes associated to human welfare considering the accelerated and unchecked population expansion, the growth in economic and industrial sectors, particularly in developing countries experiencing intensified LULC changes (Kumari, Tayyab, Hang, Khan, & Rahman, 2019). These changes have different consequences for both human society and the environment, including increased vulnerability to flooding and drought, ecosystem services losses, environmental degradation, groundwater depletion, landslide dangers, and soil erosion (S. Pal & Talukdar, 2020).

Numerous methods have been developed to identify the patterns of LULC and dynamics from satellite data and terrestrial mapping. Terrestrial mapping is a direct method that allows the map to be produced with different levels of precision, however which is a labor-intensive, expensive, and time-consuming method of mapping large areas (Langat, Kumar, Koech, & Ghosh, 2019). On the other hand, LULC mapping using satellite and aerial photography is affordable, multi-temporal, geographically broad, and time-saving (Hoffmann, 2005). Remote scanning enables the rapid compilation of information about LULC at lower cost than other methods. For LULC mapping, satellite images offer the benefits of extensive spatial coverage and multi-temporal availability (Chen & Wang, 2010). With the improvement of multispectral satellite sensors, the significance of the application of remote sensing has been increased continuously in the research arena and for planning purposes (Stefanov & Netzband, 2005).

In recent times, the ML methods on remotely sensed imageries for LULC mapping has been gaining ground (Maxwell, Warner, & Fang, 2018). The two subtypes of ML techniques are supervised and unsupervised techniques. (Wu, Zhu, Lawes, Dunkerley, & Zhang, 2019). Many researchers identified that supervised classification perform better than unsupervised classification and it is more desirable as in this classification technique researcher have full control over the classification (Lu & Weng, 2007). Over the last decade, innovative algorithms such as SVM, KNN, RF, decision tree, and others have received huge attention in the applications, such as LULC classification (Ma et al., 2019). Thus, various studies on LULC modeling have been undertaken, both using and comparing different ML techniques (Talukdar et al., 2020). Additionally, several experiments have been performed to identify the most appropriate ML algorithms for LULC mapping (Camargo, Sano, Almeida, Mura, & Almeida, 2019). There is evidence to suggest SVM, KNN and RF typically offers greater accuracy as compared to other conventional classifier algorithms (Carranza-García, García-Gutiérrez, & Riquelme, 2019), while SVM and RF are the most effective ML methods for LULC classification when compared to all other methods (Ma et al., 2019). In context of Bangladesh (Rahman et al., 2020; Torit Chakraborty, 2019) in their paper shown that SVM performed better than RF, DT and KNN in LULC classification and KNN perform better after SVM. The paper related to the LULC classification based on ML algorithms in context of Bangladesh is limited. But many researchers used SMV, KNN as LULC modelling and with a high accuracy. So, the optimum LULC classification algorithm is remain hindered that which classifier perform better with higher accuracy. But the precision of LULC classification depends on the sensor properties and elements connected to image data, such as spatial and temporal resolution. (Deng, Wang, Deng, & Qi, 2008).

Numerous investigations have identified that the LULC classification method based on medium- and low-resolution satellite images suffers from many spectral and geographical limitations that reduce its precision (S. Pal & Talukdar, 2020). For this reason, ML methods are gaining importance to get around the foregoing limitation and produce high-precision LULC calculation. In addition, given that successful outcomes depend greatly on the selection of the ML model, training data, and input parameters, whereas the precision level is not same for all ML methods (Dutta, Rahman, Paul, & Kundu, 2019). Numerous studies are conducted on LULC classification using ML methods, but the effectiveness of the models has not been thoroughly examined. This study compares four ML techniques to determine the methods which can yield better accuracies.

## Materials and Methods

### *Study Area*

This study accommodates Khulna city and its surrounding area. It is located at the southwestern part of Bangladesh. The population of Khulna city, according to (BBS, 2011), is 0.66 million. In terms of earthquake, cyclone, and flood danger, Khulna is comparatively located in a low-risk area. However, Khulna might experience immediate effects from any sea level rise. A range of strategic elements contribute to the city's importance. First, the city has crucial connections to the country's second seaport, Mongla port. Additionally, the city has a significant industrial base. Last but not least, Khulna serves as the primary hub for export-processing industries related to shrimp farming, which is practically Bangladesh's second-largest demand for foreign exchange after ready-made clothing. According to (KDA, 2000), there are around 11,280 acres of land in the KCC core region. Almost 0% of these lands are not yet being used for urban purposes. This indicates that KCC has around 1100 acres of land accessible for future urban development. At present the city growing faster in the eastern and southern part which captured agricultural and barren land.

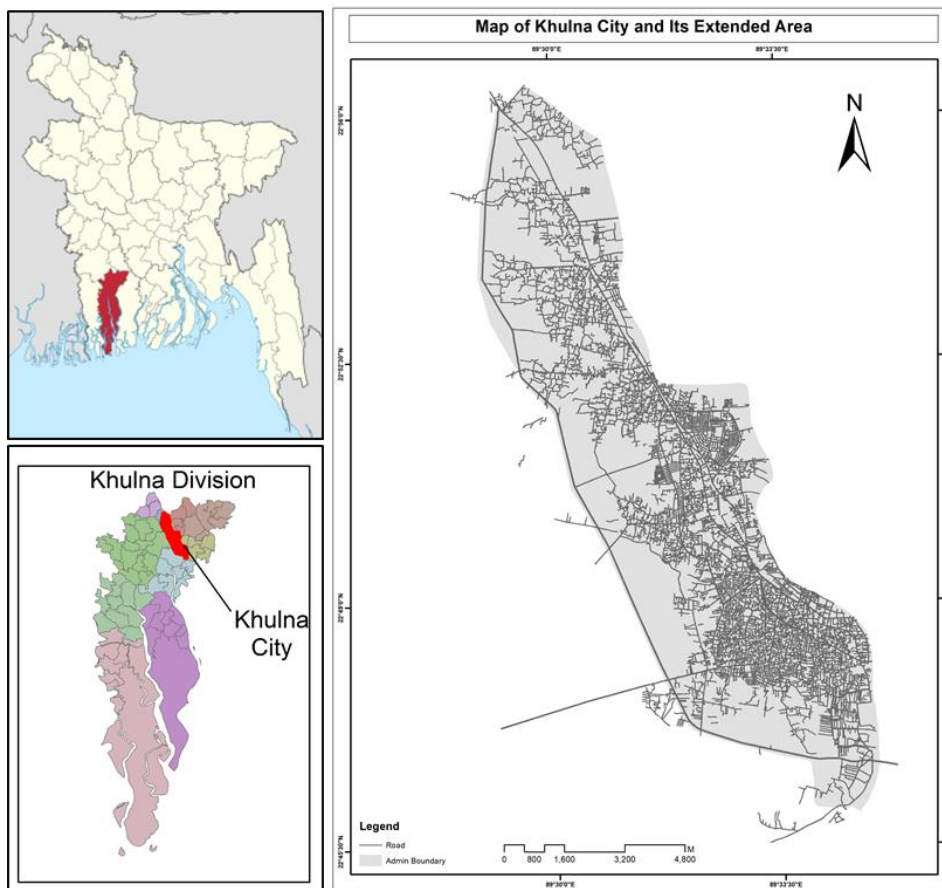


Figure 1. Map of the study area

### *Methods for LULC Classification*

Shih (2019) in his research concluded that SVM performed the best on simulated and actual satellite data as it is based on structural risk minimization (SRM) principle. As an object method KNN performs better in low-resolution satellite image classification (Tehrany et al., 2014). KNN can predict without the requirement for training, and new data can be added without affecting the system's precision. (Samaniego et al., 2009). The tree analogy of DT classifier used in categorical data and classification is extremely rapid once the model is established, as no additional complex mathematics is necessary (M. Pal & Mather, 2003). It can analyze a wide range of data kinds, including numerical data and satellite photos. It is a group learning system based on decision trees that incorporates massive ensembles of classification and regression trees (Camargo et al., 2019). In this research, the LULC classification has been completed using the four most popular ML classifiers which has several advantages in image segmentation/ classification. Each classifier has its own parameters which is set during the time of model development in QGIS software.

#### Support vector machine (SVM)

SVM was first developed to address problems of binary classification (Maxwell et al., 2018). It is developed on the SRM principle. It classifies data points using a hyper-spectral plane. In the time of this process, the margin width is kept maximum according to the vectors (Bouaziz et al. 2017). SVM supports a wide range of continuous and categorical variables along with linear and non-linear samples with various levels of class membership. Support vectors are the bordering samples that define the SVM's margin or hyperplane (Shih, Stow, & Tsai, 2019). Although polynomial and radial basis function (RBF) kernels have been used most frequently in remote sensing (Adam, Mutanga, Odindi, & Abdel-Rahman, 2014), RBF is the most preferred methodology for LULC classification because it is more accurate than the other traditional methods.

Since the purpose of SVM is to identify the best separating hyper-plane among the available hyper-planes, the original SVM approach commences with a collection of data and aims to discover the hyper-plane that can divide the datasets into a number of classes. To effectively build hyperplanes and reduce classification errors, the SVM technique also needs a good kernel function (Awad & Khanna, 2015). The kernel type utilized in the SVM approach is critical. The SVM's functionality is mostly determined by the kernel size, whereas the similarity of a smooth surface is determined by the higher kernel density. The genetically optimized SVM performs best on simulated and real-world hyperspectral satellite data (Shih et al., 2019). SVM's principal job is to delineate the ideal boundary that maximizes the separation between the complete set of support vectors.

#### K- nearest neighbor (KNN)

The k-NN classifier is separate from other classifiers because it is not trained to create a model. Rather than that, each unidentified sample is directly compared to the training data. The unknown sample is assigned to the most frequent class of the k training samples that are closest to the feature space. As a result, a low k number produces a choice boundary that is extremely intricate, whereas a higher k value produces a decision boundary that is more generic. As the quantity of training samples increases, it is anticipated that k-NN classification will use more resources because there isn't a trained model (Maselli, Chirici, Bottai, Corona, & Marchetti, 2005).

#### Decision tree (DT)

One of the most logically straightforward ML classifiers is the DT. It is a method for recursively splitting the supplied data. For instance, the data could be segmented according to whether the value in a particular band is more than or less than a threshold. With branches representing the routes between splits and leaves representing the ultimate target values, a tree analogy is employed to explain the general pattern of repeating splits. In a classification tree, the values of leaf represent classes; whereas in a regression tree, it stands for a continuous variable (M. Pal & Mather, 2003).

The logic for model can be represented visually as a collection of if-then rules. DTs may be used with categorical data, and classification is extremely rapid once the model is established, as no additional complex mathematics is necessary. DTs have a number of drawbacks, including the likelihood of generating an inefficient solution and overfitting. Usually, tree trimming is used to remedy the latter, which entails eliminating one or more splitting layers (i.e. branches). Pruning declines the classification accuracy for training data but rises the accuracy for handling unknowns in general (M. Pal & Mather, 2003).

#### Random forest (RF)

The RF algorithm has been extensively used to address environmental issues such as hydrological resource and disaster management. It is capable of processing a wide variety of data types, including satellite images and numerical data (Camargo et al., 2019). It is a decision tree-based ensemble learning system that combines huge ensemble regression and classification trees. Two parameters are required to configure the RF model, they are referred to as the method's base parameters. These are (1) the number of trees, which is explicable by the "n-tree" method, and (2) the number of features in each split, which is explicable by the "m-try" method. Classification trees offer each individual the ability to choose or vote, and they accurately classify the trees in the entire forest to control the majority vote.

Several recent researches have demonstrated an acceptable performance for LULC classification utilizing RF in distant sensing applications (Adam et al., 2014). This method's large number of trees improves accuracy (Feng et al., 2015) and land-use modeling.

Table 1. Description of the LULC classes identified.

| Class Name                  | Class Description                                    |
|-----------------------------|--|
| Built up area               | Area which is covered by settlement, road            |
| Wetlands                    | Area covered by water                                |
| Agriculture and Vacant land | Area covered by crop land, vegetation, & open space. |

#### *Data description*

Landsat satellite imageries (downloaded from USGS EarthExplorer website) are used in this study. To avoid the influence of seasonal variation, all images are dated between November to March. Maximum cloud coverage was 10%. Due to the lack of radiometric and geometric imperfections in Landsat satellite data, no extra georectification or image-to-image registration was required during image pre-processing.

#### Data Preparation for Classifiers

Since the image dataset is 8-bit, pixels values range between 0 and 255. These pixels values are normalized to 0-1 using following equation-

$$X = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

The classifier's target variable was this binary category class. Based on the training data, all the ML algorithms (SMV, KNN, DT, and RF) were performed to classify using Orfeo ToolBox's learning tool.

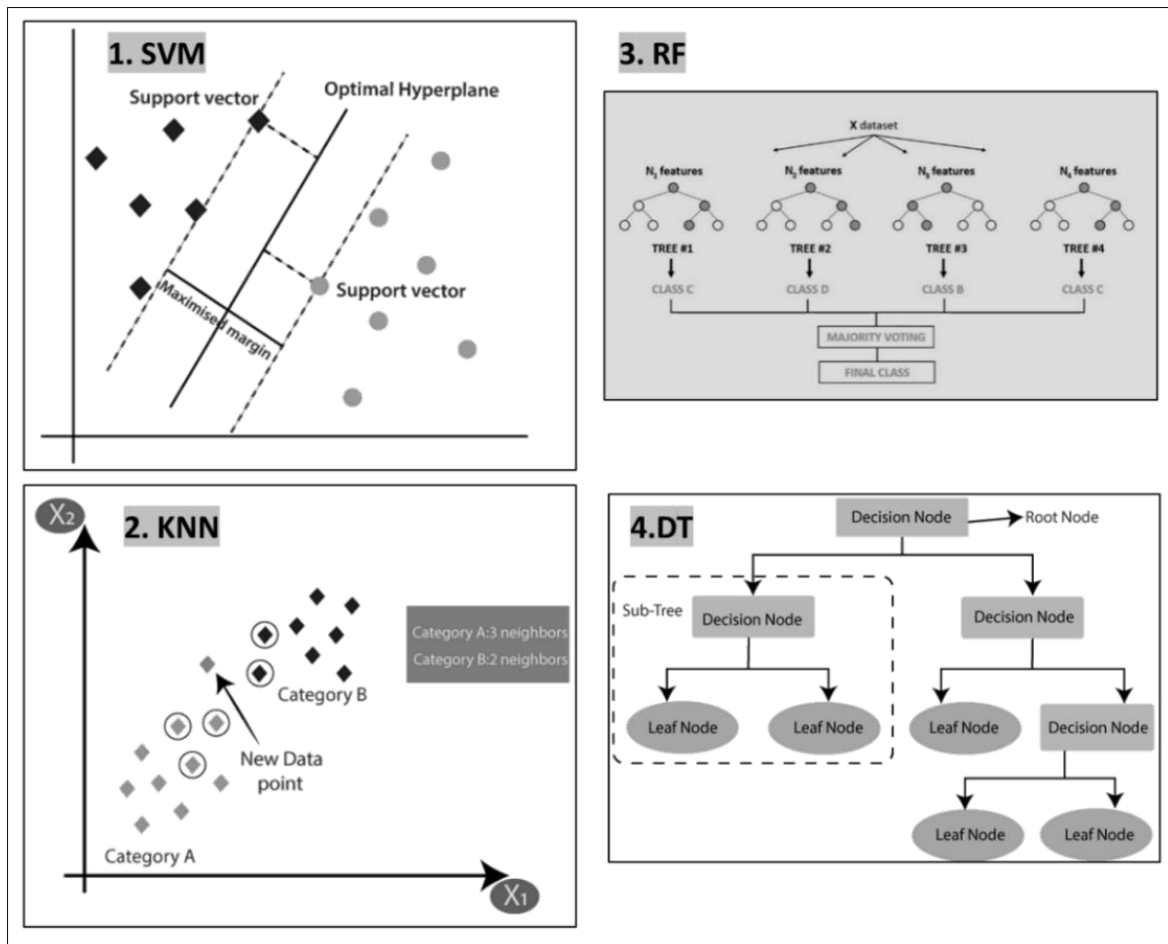


Figure 2. Schematic architecture of land use land cover classifiers 1. SVM, 2. KNN, 3. RF and 4. DT

### Multi-temporal land cover mapping

The collected satellite data is processed including staking and clipping based on the area of interest (Khulna extended city area). In layer staking Band 4, 5, and 6 is used to classify into three class (built-up, wetland and agriculture & vacant). Total number of the pixels are 87000 it could be also calling the total amount of data. The data is trained with 1672 pixels. Based on the three-category image were classified using these four ML algorithms in qgis software. The accuracy of land cover maps was determined by comparing them to 545 ground realities derived from Google Earth images which is also called test data. These 545 pixels were selected using the random sampling method. The Kappa statistics and confusion matrix, which are generally regarded as the best quantitative indicators of image classification accuracy, were produced for accuracy assessment.

### Validation Technique

Two methods of model performance validation are used; overall accuracy (Roy et al. 2015) and kappa statistics (Shao et al. 2012). Kappa is the widely accepted validation technique of image classification (Ma et al., 2019; Talukdar et al., 2020; Rahman et al., 2020). The equation of Cohen kappa is-

$$K = \frac{P_o - P_e}{1 - P_e} \quad (2)$$

where,  $P_o$  = relative observed agreement among raters and  $P_e$  = the potential likelihood of coincidence. The perfect agreement between two raters is represented by 1. The sum of samples that were properly predicted divided by the total number of test samples denotes overall accuracy. Equation of overall accuracy is-

$$\text{Overall Accuracy} = \frac{O}{n} \quad (3)$$

where,  $O$  = number of correctly predicted pixels and  $n$  = total number of test data.

### Results

The following section of this paper is discussed the results of the for ML based classification methods. Among the four classifiers, the result shows that SVM performs better in terms of low pixel-based satellite image classification.

#### *Classification Statistics*

The image was classified based on four ML algorithms. Each of classified image shown higher accuracy of classification. Among the four algorithms SVM shown the highest level of accuracy which overall accuracy is 90.74% and cohen kappa is 84%. KNN and RF perform better but the accuracy of DT is lower than the others. KNN shown the overall accuracy 90.05% and where cohen kappa is 82.99%. It is seen that both SVM and KNN performed better in pixel based LULC image classification. The other two shown relatively low accuracy level as mentioned in table 2, 3, 4 and 5.

Table 2. SVM classification statistics

| <b>Error matrix</b>       | <b>Class</b>         | <b>Built-up</b> | <b>Wetland</b> | <b>Agriculture &amp; Vacant</b> | <b>Total</b> |
|---------------------------|----------------------|-----------------|----------------|---------------------------------|--------------|
|                           | Built-up             | 266             | 0              | 18                              | 284          |
|                           | Wetland              | 0               | 82             | 16                              | 98           |
|                           | Agriculture & Vacant | 8               | 7              | 148                             | 163          |
|                           | Total                | 274             | 89             | 182                             | 545          |
| <b>Validation results</b> | Producer's accuracy  | 90.68%          | 81.03%         | 93.02%                          | -            |
|                           | User's accuracy      | 93.66%          | 83.67%         | 90.8%                           | -            |
|                           | Overall accuracy     | 90.74%          |                |                                 |              |
|                           | Cohen Kappa          | 84.00%          |                |                                 |              |

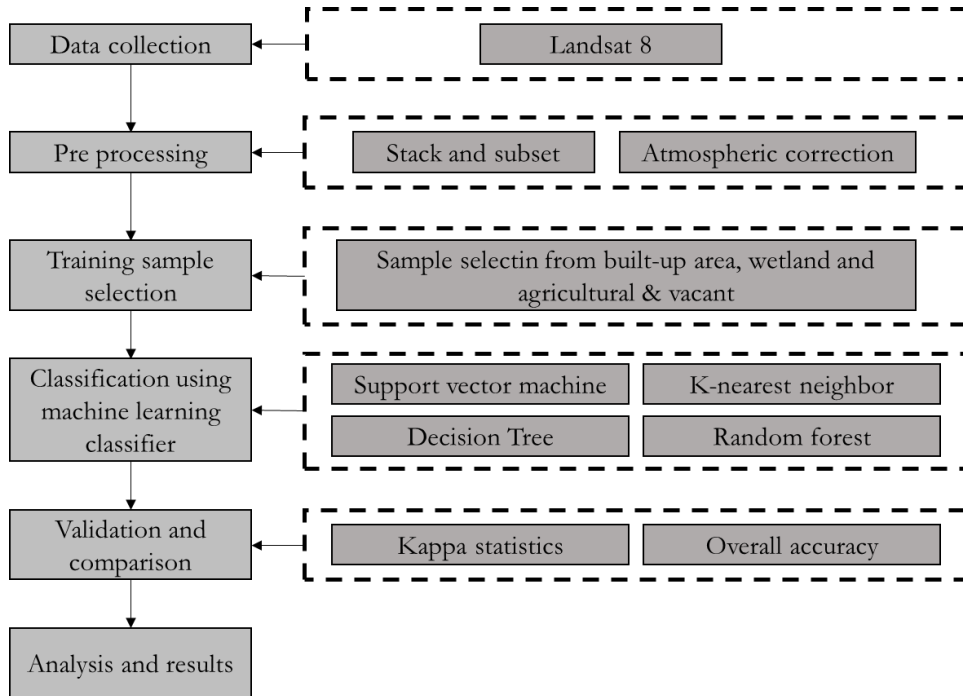


Figure 3. Flowchart of the methodology

Table 3. KNN classification statistics

|                           | Class               | Built-up | Wetland | Agriculture & Vacant | Total |
|---------------------------|---------------------|----------|---------|----------------------|-------|
|                           | <b>Error matrix</b> | Built-up | 269     | 0                    | 31    |
| Wetland                   |                     | 0        | 82      | 16                   | 98    |
| Agriculture & Vacant      |                     | 5        | 7       | 135                  | 147   |
| Total                     |                     | 274      | 89      | 182                  | 545   |
| <b>Validation results</b> | Producer's accuracy | 94.53%   | 80.85%  | 89.56%               | -     |
|                           | User's accuracy     | 89.67%   | 83.67%  | 91.84%               | -     |
|                           | Overall accuracy    | 90.05%   |         |                      |       |
|                           | Cohen Kappa         | 82.99%   |         |                      |       |

RF's image classification statistics has been shown that overall accuracy of this algorithm is 87.62% and cohen kappa is 78.24%. The last algorithm of this study, which is DT shown lower level of accuracy compare to the other three algorithms. The overall accuracy in LULC classification based on this algorithm shown 85.51% and cohen kappa is about 74.46%. Which denoted that, both RF and DT not performed well compared to SVM

and KNN classifiers. Based on the visual analysis it has seen that SVM and KNN has the excellent ability in pixel-based image classification, on the other hand RF and DT shown more compact classification.

Table 4. RF classification statistics

| <b>Error matrix</b>       | <b>Class</b>         | <b>Built-up</b> | <b>Wetland</b> | <b>Agriculture &amp; Vacant</b> | <b>Total</b> |
|---------------------------|----------------------|-----------------|----------------|---------------------------------|--------------|
|                           | Built-up             | 269             | 0              | 38                              | 307          |
|                           | Wetland              | 0               | 78             | 16                              | 94           |
|                           | Agriculture & Vacant | 5               | 11             | 128                             | 144          |
|                           | Total                | 274             | 89             | 182                             | 545          |
| <b>Validation results</b> | Producer's accuracy  | 92.47%          | 69.15%         | 90.31%                          | -            |
|                           | User's accuracy      | 87.62%          | 82.98%         | 88.89%                          | -            |
|                           | Overall accuracy     | 87.62%          |                |                                 |              |
|                           | Cohen Kappa          | 78.24%          |                |                                 |              |

Table 5. DT classification statistics

| <b>Error matrix</b>       | <b>Class</b>         | <b>Built-up</b> | <b>Wetland</b> | <b>Agriculture &amp; Vacant</b> | <b>Total</b> |
|---------------------------|----------------------|-----------------|----------------|---------------------------------|--------------|
|                           | Built-up             | 250             | 0              | 8                               | 258          |
|                           | Wetland              | 0               | 76             | 16                              | 92           |
|                           | Agriculture & Vacant | 24              | 13             | 158                             | 195          |
|                           | Total                | 274             | 89             | 182                             | 545          |
| <b>Validation results</b> | Producer's accuracy  | 77.58%          | 69.14%         | 94.73%                          | -            |
|                           | User's accuracy      | 96.90%          | 82.61%         | 81.03%                          | -            |
|                           | Overall accuracy     | 85.51%          |                |                                 |              |
|                           | Cohen Kappa          | 74.46%          |                |                                 |              |

*Comparison among the classifiers*

It is clear that, all the ML classifiers perform better in terms of low pixel-based satellite image classification. As shown in sub-section 3.1, according to precision score, all algorithms work excellently. But, it is seen that SVM performed better among these four algorithms. KNN got the second position in this case of study (Figure 4). The other two classifiers named RF and DT perform not as SVM and KNN.

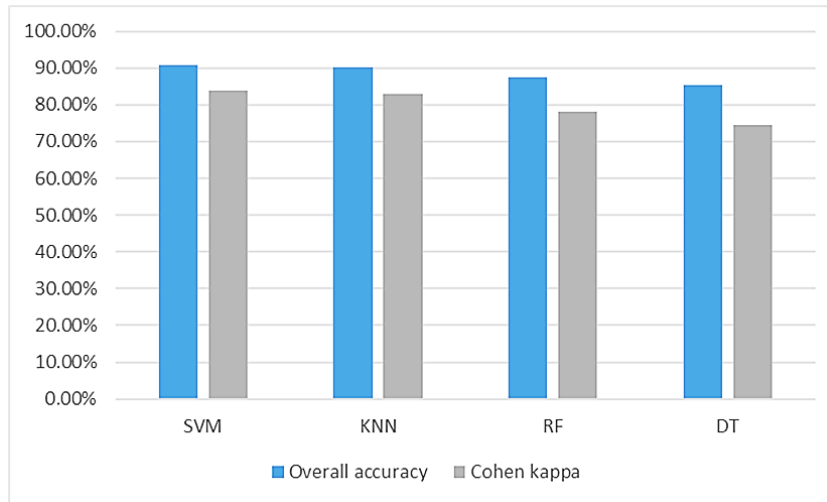


Figure 4. Validation results statistics

Based on the visual analysis (Figure 5), it has been seen that at the upper left corner image named classified image using SVM algorithms and upper right corner image named classified image using KNN algorithm has the excellent ability in pixel-based image classification as it shows more compact classification, on the other hand RF and DT can't performed well.

## Discussion

Traditional LULC classification methods based on pixel digital numbers are inaccurate because multi-scale image segmentation cannot be used to segment images (Jebur, Mohd Shafri, Pradhan, & Tehrany, 2014). Four well-known ML techniques were used in the current research to assess the precision of the LULC classification method utilizing multispectral Landsat imagery. The result clearly indicates that both SVM and KNN performed better in low-resolution based satellite image classification than other two ML algorithms. The same result is found in Carranza-García's research that SVM, and KNN typically offers greater accuracy, when compared to other conventional classifier techniques (Carranza-García et al., 2019), (Ma et al., 2019) also proved that with comarision to all other ML approaches, SVM is the best technique for LULC classification. (Jebur et al., 2014) in his research also shown that SVM performed better in terms of low-pixel based satellite image classification. So, SVM can be utilized in low pixel-based satellite image classification and can be used for further stage of modelling and planning.

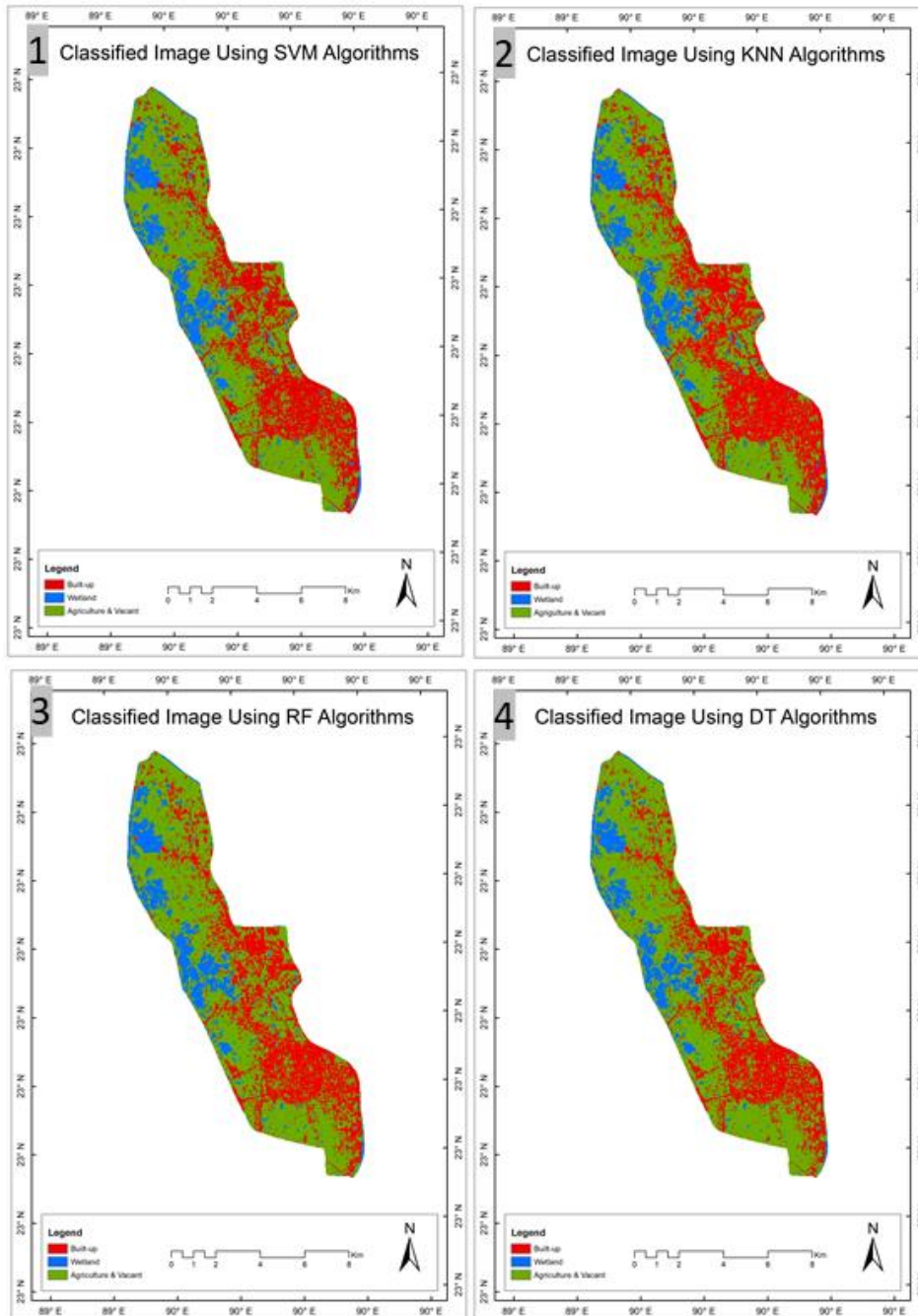


Figure 5. Classified images using 1. SVM, 2. KNN, 3. RF and 4. DT

## Conclusion

This study has been done in order to observe the accuracy of different ML classifiers for the preparation of LULC map using satellite imageries. Accuracy assessments have been undertaken by using the Kappa statistics and overall accuracy. According to the results, the area under each LULC class differs depending on the classifier. The accuracy of the classifiers is found to vary insignificantly, but this slight difference has a significant impact on LULC mapping and planning. Aim of this study is fulfilled according to the result of the analysis. SVM has been applied to segmentize low resolution (30 m) satellite image and the final result shows that it has better ability compare to the other three ML algorithms. Form the classification statistics it can be said that both SVM and KNN can be the better alternative classification algorithm especially for low resolution satellite image as their accuracy is higher (both accuracies are above 80%) than the other two algorithms. So, it can be concluded that SVM can be use as low-resolution pixel-based satellite image classification and further in LULC change modelling.

## References

- Adam, E., Mutanga, O., Odindi, J., & Abdel-Rahman, E. M. (2014). Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing*, 35(10), 3440-3458.
- Awad, M., & Khanna, R. (2015). Support vector machines for classification. In *Efficient Learning Machines* (pp. 39-66): Springer.
- BBS. (2011). *Population and housing census 2011*. Dhaka: Government republic of Bangladesh
- Bouaziz, M., Eisold, S., & Guermazi, E. (2017). Semiautomatic approach for land cover classification: a remote sensing study for arid climate in southeastern Tunisia. *Euro-Mediterranean Journal for Environmental Integration*, 2(1), 1-7.
- Camargo, F. F., Sano, E. E., Almeida, C. M., Mura, J. C., & Almeida, T. (2019). A comparative assessment of machine-learning techniques for land use and land cover classification of the Brazilian tropical savanna using ALOS-2/PALSAR-2 polarimetric images. *Remote Sensing*, 11(13), 1600.
- Carranza-García, M., García-Gutiérrez, J., & Riquelme, J. C. (2019). A framework for evaluating land use and land cover classification using convolutional neural networks. *Remote Sensing*, 11(3), 274.
- Chen, Z., & Wang, J. (2010). Land use and land cover change detection using satellite remote sensing techniques in the mountainous Three Gorges Area, China. *International Journal of Remote Sensing*, 31(6), 1519-1542.
- Deng, J., Wang, K., Deng, Y., & Qi, G. (2008). PCA-based land-use change detection and analysis using multitemporal and multisensor satellite data. *International Journal of Remote Sensing*, 29(16), 4823-4838.
- Dutta, D., Rahman, A., Paul, S., & Kundu, A. (2019). Changing pattern of urban landscape and its effect on land surface temperature in and around Delhi. *Environmental monitoring assessment*, 191(9), 1-15.
- Feng, Q., Gong, J., Liu, J., & Li, Y. (2015). Flood mapping based on multiple endmember spectral mixture analysis and random forest classifier—The case of Yuyao, China. *Remote Sensing*, 7(9), 12539-12562.
- Hoffmann, J. (2005). The future of satellite remote sensing in hydrogeology. *Hydrogeology Journal*, 13(1), 247-250.

- Jebur, M. N., Mohd Shafri, H. Z., Pradhan, B., & Tehrany, M. S. (2014). Per-pixel and object-oriented classification methods for mapping urban land cover extraction using SPOT 5 imagery. *Geocarto International*, 29(7), 792-806.
- KDA. (2000). *Urban Strategy (2002-2005)*. Retrieved from
- Kumari, B., Tayyab, M., Hang, H. T., Khan, M. F., & Rahman, A. (2019). Assessment of public open spaces (POS) and landscape quality based on per capita POS index in Delhi, India. *SN Applied Sciences*, 1(4), 1-13.
- Langat, P. K., Kumar, L., Koech, R., & Ghosh, M. K. (2019). Monitoring of land use/land-cover dynamics using remote sensing: A case of Tana River Basin, Kenya. *Geocarto International*, 1-19.
- Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, 28(5), 823-870.
- Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., & Johnson, B. A. (2019). Deep learning in remote sensing applications: A meta-analysis and review. *ISPRS journal of photogrammetry remote sensing*, 152, 166-177.
- Mas, J.-F., Lemoine-Rodríguez, R., González-López, R., López-Sánchez, J., Piña-Garduño, A., & Herrera-Flores, E. (2017). Land use/land cover change detection combining automatic processing and visual interpretation. *European Journal of Remote Sensing*, 50(1), 626-635.
- Maselli, F., Chirici, G., Bottai, L., Corona, P., & Marchetti, M. (2005). Estimation of Mediterranean forest attributes by the application of k-NN procedures to multitemporal Landsat ETM+ images. *International Journal of Remote Sensing*, 26(17), 3781-3796.
- Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 39(9), 2784-2817.
- Pal, M., & Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote sensing of Environment*, 86(4), 554-565.
- Pal, S., & Talukdar, S. (2020). Assessing the role of hydrological modifications on land use/land cover dynamics in Punarbhaba river basin of Indo-Bangladesh. *Environment, Development and Sustainability*, 22(1), 363-382.
- Rahman, A., Abdullah, H. M., Tanzir, M. T., Hossain, M. J., Khan, B. M., Miah, M. G., . . . Environment. (2020). Performance of different machine learning algorithms on satellite image classification in rural and urban setup. *Remote Sensing Applications: Society*, 20, 100410.
- Reis, S. (2008). Analyzing land use/land cover changes using remote sensing and GIS in Rize, North-East Turkey. *Remote Sensing*, 8(10), 6188-6202.
- Roy, S., Farzana, K., Papia, M., & Hasan, M. (2015). Monitoring and prediction of land use/land cover change using the integration of Markov chain model and cellular automation in the Southeastern Tertiary Hilly Area of Bangladesh. *Int. J. Sci. Basic Appl. Res*, 24, 125-148.
- Samaniego, L., & Schulz, K. (2009). Supervised classification of agricultural land cover using a modified k-NN technique (MNN) and Landsat remote sensing imagery. *Remote Sensing*, 1(4), 875-895.
- Scornet, E., Biau, G., & Vert, J.-P. (2015). Consistency of random forests. *The Annals of Statistics*, 43(4), 1716-1741.

- Hasan, M. Z. et al., (2022). Comparative Assessment of Machine Learning Algorithms for Land Use and Land Cover Classification Using Multispectral Remote Sensing Image. *Khulna University Studies*, Special Issue (ICSTEM4IR): 33-46.
- Shao, Y., & Lunetta, R. S. (2012). Comparison of support vector machine, neural network, and CART algorithms for the land-cover classification using limited training data points. *ISPRS Journal of Photogrammetry and Remote Sensing*, 70, 78-87.
- Shih, H.-c., Stow, D. A., & Tsai, Y. H. (2019). Guidance on and comparison of machine learning classifiers for Landsat-based land cover and land use mapping. *International Journal of Remote Sensing*, 40(4), 1248-1274.
- Stefanov, W. L., & Netzband, M. (2005). Assessment of ASTER land cover and MODIS NDVI data at multiple scales for ecological characterization of an arid urban center. *Remote sensing of Environment*, 99(1-2), 31-43.
- Talukdar, S., Singha, P., Mahato, S., Praveen, B., & Rahman, A. (2020). Dynamics of ecosystem services (ESs) in response to land use land cover (LU/LC) changes in the lower Gangetic plain of India. *Ecological Indicators*, 112, 106121.
- Tehrany, M. S., Pradhan, B., & Jebuv, M. N. (2014). A comparative assessment between object and pixel-based classification approaches for land use/land cover mapping using SPOT 5 imagery. *Geocarto International*, 29(4), 351-369.
- Torit Chakraborty. (2019). *Land Cover Classification from Multispectral Remote Sensing Image Using Deep Neural Network, K-Nearest Neighbor, Decision Tree and SVM Algorithms: A machine learning based comparison approach*. Paper presented at the 1st International Conference on Urban and Regional Planning, Bangladesh, Dhaka.
- Wu, L., Zhu, X., Lawes, R., Dunkerley, D., & Zhang, H. (2019). Comparison of machine learning algorithms for classification of LiDAR points for characterization of canola canopy structure. *International Journal of Remote Sensing*, 40(15), 5973-5991.