Assessing the factors affecting building construction collapse casualty using machine learning techniques: a case of Lagos, Nigeria

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Abstract

Building construction collapse in Nigeria has become a subject of international concern in recent times due to numerous lives and properties being wasted yearly. This study presents a brief statistical report of building collapse in Nigeria from 2000–2021, using Lagos State as a case study and conducts a comparative analysis using five supervised machine learning algorithms, namely Robust Linear Model (RLM), Support Vector Machine (SVM), K Nearest Neigbours (KNN), Random Forest (RF) and Decision Tree (DT) for predicting the rate of casualty from building collapse in Lagos Nigeria. Feature importance was performed to determine the most relevant factors that causes building construction collapse casualty. The result shows that the Support Vector Machine (SVM) algorithm has the best forecasting performance among the other algorithms considered. Feature importance analysis, using the SVM model ranked the factors affecting building construction collapse in order of relevance and 'location' is considered the most relevant factor contributing to building collapse casualty in Nigeria. Results from this study are important for policy makers and the study recommends that proper onsite geo-technical inspection should be done on site locations before commencement of building constructions in Nigeria.

Keywords: Building collapse; site location; Lagos; feature importance; machine learning

Introduction

Buildings or shelters are fundamental needs of all humans. According to the SDG 11: Sustainable cities and communities (UNEP 2022), safe and inexpensive housing should be realized by 2030 in all the united nation countries including Nigeria. Building collapse has become a major menace in Nigeria in recent times. Nigeria is popularly referred to as the 'Giant of Africa', which is situated in the western coastline of Africa. The country has the largest economy in Africa, being a crude oil producing nation and the home of several business tycoons. Nigeria is renowned for her diverse climate, culture, ethnicity and beliefs. Lagos is the smallest (land mass) and most famous state in Nigeria. It is also the business hub of Nigeria being the home to the largest seaport and airports of the nation. It is the largest city in sub-Saharan Africa and the second largest city in Africa after Cairo (Dano et al. 2020). Its population and civilization are often attributed to being the former capital of Nigeria and its location the centre of inland waterway (lagoon) adjacent the Atlantic Ocean through which ancient slave trade was practiced (Dano et al. 2020).

Lagos boasts of so many buildings which occupies its small land mass. Pathetically, the rate of building collapse in Lagos in recent times has been on an alarming increase, although building collapse occurs in other underdeveloped, developing and developed nations of the world. However, the frequency of its occurrence and the safety level involved in Lagos is frightening, and this calls for critical investigation on the causes of the collapse and the casualty level. The map of Lagos with the local governments is shown in Figure 1. The island area where majority of the building collapse occurs in Nigeria is shown in pink colour.

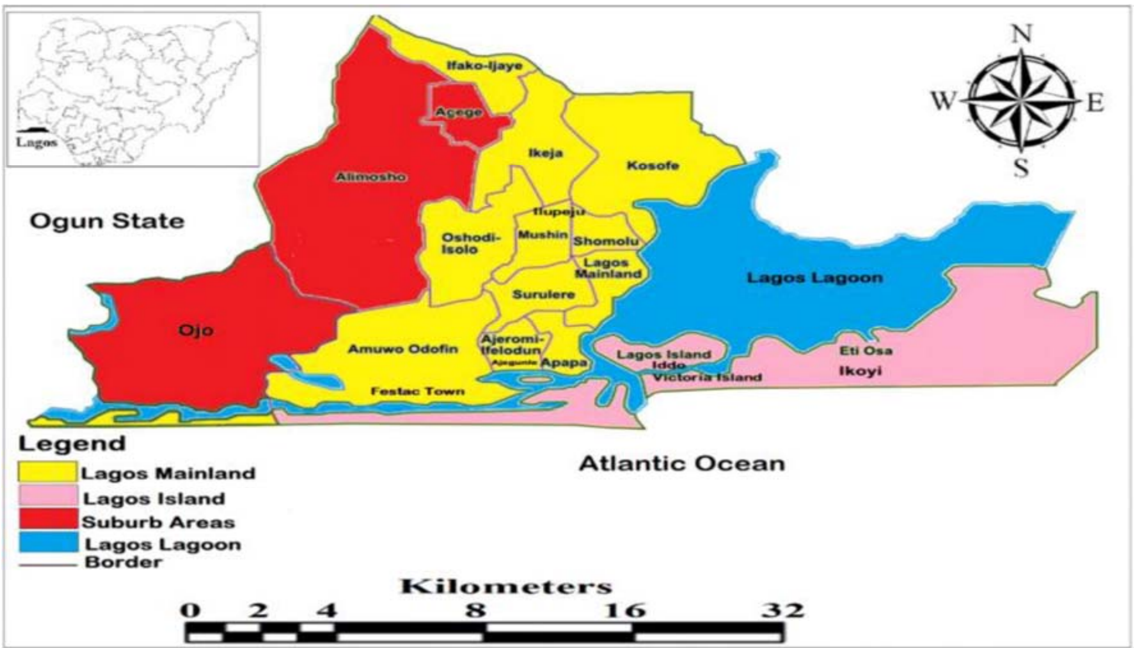

Figure 1. Map of Lagos, Nigeria. (Source: Dano et al. (2020)).

Despite the effort of the Federal Ministry of Housing and Works in Nigeria, collapse of building in the major cities of Nigeria have recurrently been devastating (Ayedun et al. 2012; Turjo et al. 2021). Building collapse has continued to occur and this ugly event has led to the casualty of several citizens and migrants in Lagos, hence, the importance of this study. Philips Akinyemi et al. (2016) studied the trend of building collapse in three major cities of Nigeria (Lagos, Port-Harcourt and Abuja). In their work, they reported that 60% of collapsed building in Nigeria transpire in Lagos state. 70% of which are private buildings, 23.3% being public buildings and 6.7% being corporate organization buildings. They emphasized that about 70% of collapsed buildings do not have approved building plans before commencement of onsite construction. In conclusion they recommend strict inspection of construction sites and enforcement of related building laws to prevent future loss.

Generally speaking, building collapse can either be caused by natural disaster (earthquakes, flood, and fire outbreak) or human errors. According to Ferrigni (2015), in his book ‘Seismic Retrofitting: Learning from Vernacular Architecture’, regions with high seismicity (Central and Eastern Asia) experience high rate of building collapse due to seismic/earthquake effect. Recent studies on seismic collapse and its devastative risk was carried out by Champion and Liel (2012), Bijelić et al. (2019) and Sediek et al. (2021). However, in developing countries

(Nigeria inclusive) where seismic effect is rarely observed, most building collapse have been attributed to human error (Windapo and Rotimi 2012). Government agencies in housing and woks have identified certain recurring human stimulated causes of these building collapse, which include: inadequate reinforcement, local explosion, sub-standard construction materials, unskilled professionals and workmanship, overloading/crowd pressure, non-compliance to building code, lack of soil/geotechnical test, defiance to building plan, poor supervision, hurried construction, poor maintenance of existing building and dilapidated building (Oloyede et al. 2010; Nkem Ede 2010; Taiwo and Afolami 2011; Windapo and Rotimi 2012; Ayedun et al. 2012; Philips Akinyemi et al. 2016; Okagbue et al. 2018). Several researchers have highlighted the most prevalent causes of building collapse in Nigeria. Their conclusion have shown that sub-standard building material is the most prevalent cause of these collapse (Nkem Ede 2010; Ayodeji 2011; Ayedun et al. 2012).

Oloke et al. (2017), investigated the impact of post-construction management methods on Nigeria's building collapse. The study outcomes show enormous abuse of building management code by both house owners and other non-professional real estate agent in charge of buildings. They recommend that routine building inspection should be conducted by government agency to prevent further occurrence of collapse. Taiwo and Afolami (2011), examined the case study of hotel building collapse that collapsed in Akure, Nigeria. They suggested effective government monitoring, penalty for collapse building owners, regular audit of existing building, adequate training, formal approval before construction among others, as some preventive actions to reduce such reoccurrence of collapse in Nigeria. Layi and Ademola (2016) carried out an analytic study of the trend of building collapse in Lagos and the factors causing this collapse. In their study they presented the distribution of building collapse in the different local government in Lagos. The study showed that 25% of building collapse in Lagos took place in Lagos Island which include reclaimed lands. The study suggests that the major cause of collapse in developing countries is lack of adequate synergy between government policy makers, professional bodies and the public.

Machine learning techniques have proved to be a reliable method of analysis, classification and forecasting in different fields of studies, which include education, banking and investment, trade, linguistics, building technology, science, engineering, robotics, medicine, etc. Its application in education has improved the learning and reduced the pressure of rigorous studies at all levels; by influencing the psychology of learning (Halde 2017). The flexibility and possibility of generating novel neural networks for solving different problems have made machine learning exceptional. Ağralı et al. (2023) and Lalmuanawma et al. (2020) developed and reviewed machine learning algorithm model which could predict SARS-CoV-2 pandemics. Extensive studies on text sentiment classification which is applicable in digital linguistics for detection of texts annotations was done by Onan and Korukoğlu (2017), Onan (2018), (2020), (2021), among others.

Machine Learning algorithms have been used by several researchers for the generation of correlations that can predict or forecast future occurrence of the understudy factors. Koh and Blum (2021) analysed the structural response of steel framed structure using the Decision Tree classifier algorithm. The algorithm was used for ranking feature importance of the factors that influences structural failure based on their feature importance scores. Random Forest and some neural network algorithms were used for analysing the seismic building damages that occur at Haiti 7.0 earthquake (Cooner et al. 2016). Hwang et al. (2022), also analyzed the performance of machine learning algorithms for predicting commercial seismic losses of steel building frame. They concluded that multi-layer feed-forward neural network detected the building damage with error less than 40% and that the Spatial features of texture and structure were more important than the spectral information. Machine learnings algorithms (Regression Model, Support Vector, Neural Networks, Deep Learning, Random Forest, Adaboost, Gradient Boosting, XGBoost and others) were used by Turjo et al. (2021) for the prediction of credit risk in the financial industry (Turjo et al. 2021). However, the use of machine algorithms for analysing the problem of building collapse in Nigeria is still scanty in literature.

In this study, a comparative analysis using different machine learning algorithms (RLM, SVM, KNN, RF and Decision Tree) for predicting the rate of casualty from building collapse in Nigeria is critically examined. Feature importance is also used to select the most relevant factor that affect building collapse casualties in Nigeria. This study would add to the burgeoning literature on building collapse in developing countries and the results herein would be a useful guide for policy makers.

Material and methods

Study area

This study takes Lagos as a case study among other states in Nigeria. Lagos is located in the south-western region of Nigeria, latitude 6° 27 ' and 6° 2 'North and longitude 2° 42 'E and 3° 2 3′ E, bounded on the west by Benin Republic, North and East by Ogun State and on the south by the Atlantic ocean ("Lagos latitude longitude" 2022). Lagos is the smallest state with the largest population in Nigeria and sub-Sahara Africa. The architecture of Lagos in recent time comprises of contemporary skyscrapers, high-rise buildings, dilapidated old buildings and few bungalows and traditional slums (Immerwahr 2007).

Data

The secondary data used in this study were sourced from existing literatures (Dimuna 2010; Ayedun et al. 2012; Samson et al., 2019), recent data were obtained from newspaper websites (Adelaja 2021; Emmanuel 2021) and web pages (Olawunmi et al. 2021). A comprehensive list of data on building collapse report in Lagos, Nigeria, in the last 20 years is presented in Appendix A. The data obtained for this study was analysed using the *caret* package in the R Software. Data were analysed using 10-fold cross validation with 3 repeats. Cross-validation is a popular resampling procedure used to evaluate machine learning models on a limited data sample. This procedure has a single parameter called k that refers to the number of groups that a given data sample is to be split into. When a specific value for k is chosen, it may be used in place of k in the reference to the model, such as $k = 10$ becoming 10-fold cross-validation. Cross-validation is primarily used in applied machine learning to estimate the performance of a supervised machine learning model on unseen data in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the fitting of the model.

Ethical statement

In keeping with the universal methodological standards, this study was carried out with observance of a high degree of ethical principles that would result in true and accurate findings (Philips Akinyemi et al. 2016). Due considerations were given to ethical implications of the whole process whenever human subjects are used in a research. Consequently, all activities involving the data gathering process in this study were treated with utmost confidentiality and ethicality, although no physical contacts were made with human subjects.

Machine learning algorithms

Statistical machine learning methods have gained tremendous popularity and applications in various fields in recent times. In this study, we compare the forecasting performance of five (5) different machine learning algorithms for the prediction of building collapse casualty in Lagos, Nigeria. We also assess and identify the most important variable affecting building collapse casualty. Machine learning algorithms compared in this study are Robust Linear Model (RLM), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Random Forest and Decision Tree (DT). A brief explanation of these algorithms is given in this section.

Robust linear model (RLM)

The robust linear model is usually the most suitable for handling data containing several outliers. This regression method overcomes that challenges posed by outliers on the traditional regression methods (ordinary least squares). It is one of the least utilized regression methods in machine learning and it requires high computational cost (Khan et al. 2007; Yu and Yao 2017).

Support-vector machine (SVM)

Support-vector Machine is a simple classical supervised machine learning algorithm that is highly preferred by several researchers as it produces significant accuracy and requires low computational cost. This algorithm can be used for both regression and classification task. The support vector machine algorithm is a non-probabilistic binary linear classifier that find a hyperplane in an n-dimensional Space (where n is the number of features) that particularly classifies the data points in order to augment the size of the gap amongst categories (Suthaharan 2016).

K-nearest neighbour algorithm (KNN)

KNN is one of the best and most widely used classification non-parametric supervised machine leaning algorithms with a variety of applications. It is used for classification; and aims at placing the data in distinct categories or classes. It is based on the idea that observations close to new data we seek to classify or predict can be obtained by calculating its closest distance to the existing datasets. One of the problems in using this algorithm is the similarity effect of all the features on classification while some features are less important to the classification. The minor features cause two records that are close to each other to be recognized far from one another. This misleads the classification process and reduces the accuracy of KNN algorithms (Kuhkan 2016; Gazalba and Reza, 2018).

Random forest (RF)

Random forest is a supervised machine learning algorithm that is generally used for classification and regression problems. It builds decision trees on different samples and takes a majority vote for classification and average in case of regression. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned (Louppe 2015; Emmanuel, 2021). Louppe (2015) further presented that the most important features of the Random Forest algorithm is that it can handle the data set containing continuous variables as in the case of regression and categorical variables as in the case of classification. This model has been reported to perform better for most classification problems.

Decision tree (DT)

Decision tree is a commonly used supervised machine learning algorithm that graphically illustrates decisions and their classification effects both qualitatively and quantitatively using decision nodes and leaves (Navada et al. 2011). The decision nodes represent the structure of the input data, while the decision leaves represent the categories of this structure. Decision tree is usually used to find missing data and can be applied in search engines and applicable in diverse fields of study. Decision tree is widely used in data mining, for the classification of categorical variables (Somvanshi et al. 2017).

Results

Collapse of buildings in Lagos ranges from bungalows to storey buildings and skyscrapers. From our study data, Lagos has an average of four (4) building collapsing per year leading to about thirty-one average casualties yearly. Figure 2 gives a hint on the frequency of casualty versus the number of collapse buildings. As presented in Figure 2, the maximum number of collapses per year occurred in 2011 with average of ten (10) buildings collapse, followed by the year 2000 and 2006 where nine (9) buildings collapsed respectively, and a lot of casualties were recorded. The highest number of casualty (140) was recorded in 2014 which occurred at Ikotun-Egbe area in Lagos mainland.

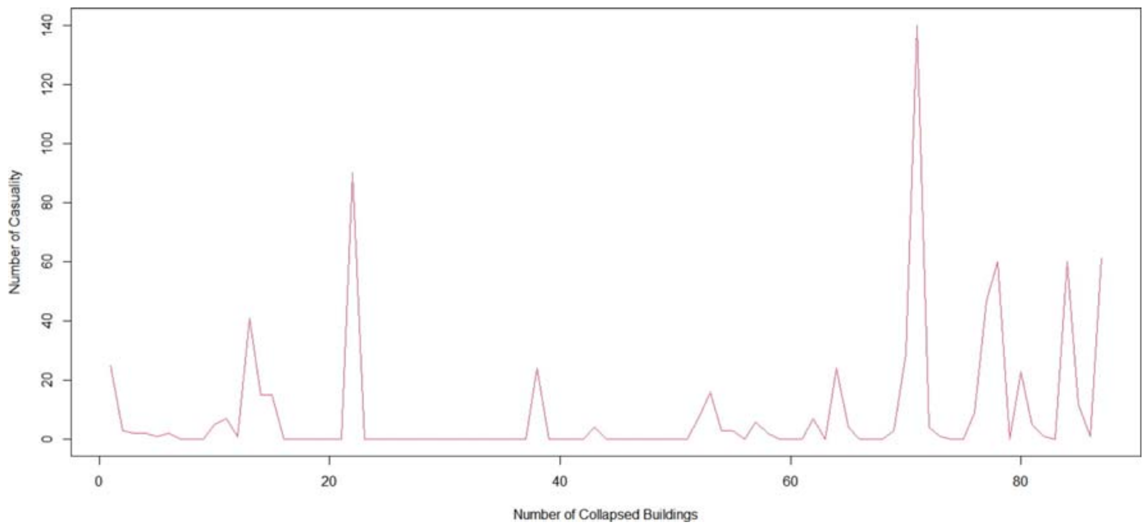

Figure 2. Line plot of Lagos building collapse casualties.

Model comparison and feature importance

In order to select the most appropriate machine learning model that will perform best with the given dataset. We investigate the forecasting performance of the five (5) machine learning algorithms. The root mean square error (RMSE) and the mean absolute error (MAE) constitutes the performance evaluation metrics. The performance metric values for the support vector machine (SVM) was the best because it has the least RMSE (17.6106) and MAE (9.3341) values as indicated in Table 1 and 2. The variable importance plot of the SVM was implemented for feature selection and the predominant variable influencing the building collapse casualties was observed to be the location of the building.

Table 1. Model performance evaluation metrics**.**

Model	RMSE	MAE
RLM	**18.0730**	**9.4469**
SVM	**17.6106**	**9.3341**
KNN	**19.1990**	**12.3278**
Random forest (RF)	**19.3692**	**12.5715**
Decision tree (DT)	**19.3302**	**12.7975**

Table 2. RMSE evaluation metrics**.**

Model	Min.	1st quart	Median	Mean	3rd quart	Maximum
RLM	3.426172	7.425092	15.62230	18.07298	21.04402	50.30788
RF	5.256837	9.627470	16.41594	19.36916	21.37394	51.95093
SVM	3.073746	7.498162	12.99626	17.61053	24.57688	52.97924
DT	7.865996	10.455674	17.27684	19.33027	20.15988	49.84799
KNN	6.639059	10.792340	16.23392	19.19898	23.37140	46.75439

Figure 3 shows block of feature plots of the explanatory variable used for predicting the number of casualties due to building collapse. The 'building' status is represented with a scale of completed buildings (1), uncompleted buildings (2) and unspecified/unreported building status (3). Although higher frequency of building collapse with casualties occurred in completed buildings, yet the casualties in uncompleted building were observed to be less frequent with a particular case being very catastrophic. Meanwhile, there are few causalities for unspecified cases of building status. Another variable is 'information' which is also divided into three: occupied buildings (1), unoccupied buildings (2) and unspecified/unreported building (3) occupancy information. The feature plot in Figure 3 shows that higher causalities were recorded in already occupied completed buildings. The number of 'Storey' plot revealed that one and four stories building have the highest frequency of collapse, however, casualties from the four-storey building collapse was greatest. For the plot on the building 'type'; commercial buildings (1), residential building (2) and the combination of both (3) were considered. Higher level of casualties was observed for commercial building collapse, both commercial and residential buildings have high frequency of building collapse. Few cases of building collapse occurred in combined buildings.

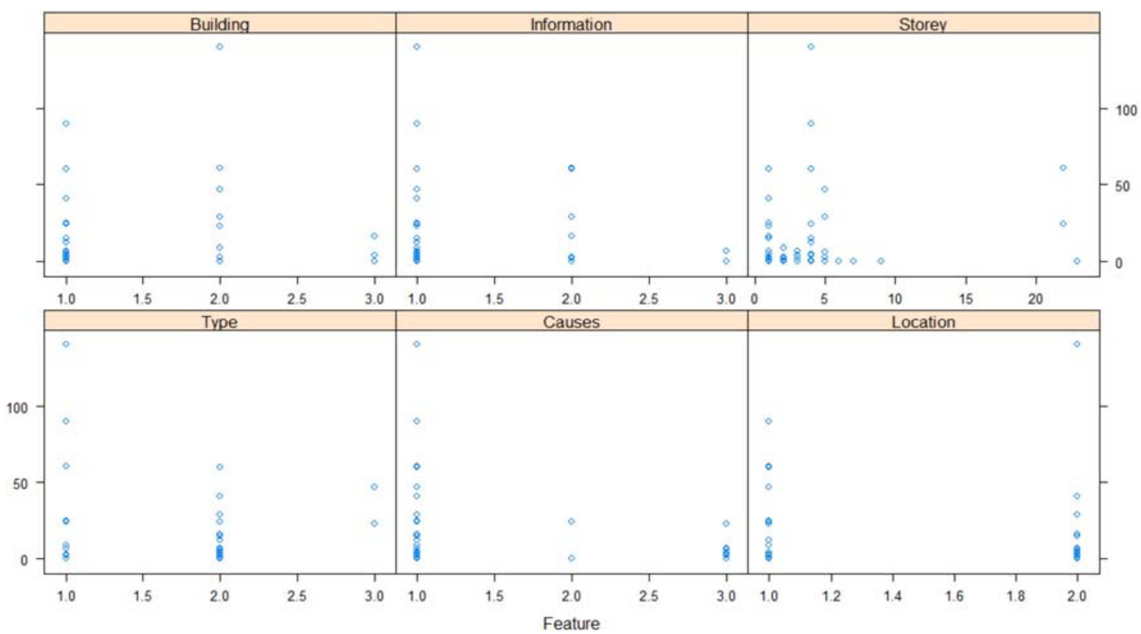

Figure 3. Feature plot of explanatory variables.

The study has classified the 'causes' of the building collapse into human factor (1), natural disaster (2) and unspecified causes (3). Human factors are sub-standard material, structural defect, onsite change of plan, bad supervision, demolition process, non-adherence to building standard and regulation, no geotechnical information, poor maintenance, construction defect, local explosion and overload. For this study, Lagos state is divided into two 'locations', namely:

Lagos Island (1) and Lagos Mainland (2) as also shown in the feature plot in Figure 3. It can be seen that more collapse of buildings occurs in the island locations than in the mainland. However, a building collapse in mainland location has the highest casualties than those in the island.

The support vector machine was used to make inference and deduce the variable importance in the study because it is the best performing model for forecasting building collapse casualty. Result of variable importance in Figure 4 clearly depicts that building location is the most important factor that influence the casualty level of building collapse in Lagos Nigeria, followed by the height of the building.

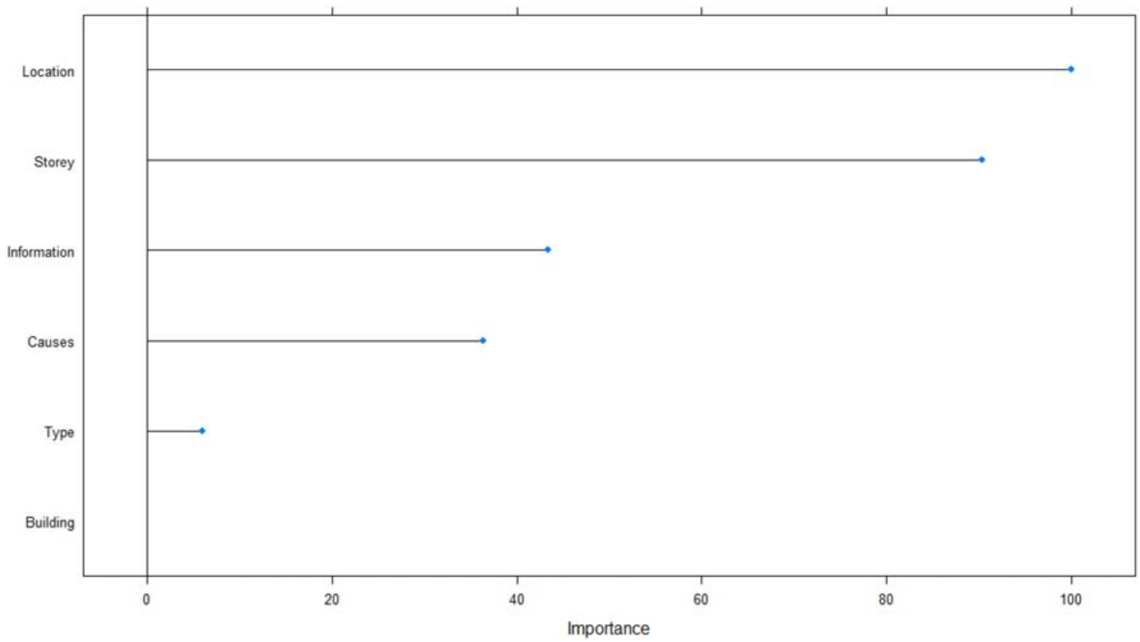

Figure 4. Variable importance plot for building collapse casualties in Lagos, Nigeria.

Discussion

This article has evaluated various predictive models for predicting building collapse casualty in Nigeria using common risk factors as predictors. Building right is very key in the growing economy of Nigeria, most especially in Lagos State which is the commercial nerve of Nigeria. Many results can be gleaned from this study. Figure 2 gives a hint of the frequency of casualty against the number of buildings collapse in Lagos, Nigeria. The highest frequency of building collapse occurred in 2011 that resulted in over 10 building collapses, over 80% occurred in the mainland while 20% occurred on the Island. As shown in Table 1 and Appendix A, year 2014 has the highest numbers of casualty (104). Having investigated the forecasting performance using five (5) machine learning algorithms, the root mean square error (RMSE) and the mean absolute error (MAE) constitutes the performance evaluation metrics. The predictive performance of the support vector machine (SVM) is the best because it has the least RMSE (17.6106) and MAE (9.3341) values as indicated in Tables 1 and 2. The variable importance plot of the SVM was implemented for feature selection and the predominant variable influencing the building collapse casualties was observed to be the location of the building. Based on this study, Lagos state is divided into two ‘locations’, namely: Lagos Island

and Lagos Mainland it is also shown in the feature plot in Figure 3. It is validated that more collapse of buildings occurs in the island locations than in the mainland. However, building collapse in mainland location has the highest casualties than those in the island, reason being that cost of purchasing land in the mainland is cheaper compared to that of the island, furthermore the geological properties of soil in the mainland is good to bear the loads of building to certain level compared to the geotechnical properties of soil in the island which has very poor bearing capacity of soil.

This basic reason encourages many land owners in the mainland area to ignore basic geotechnical properties of soil test, their assumption led to much building collapse in the mainland, which has led to many casualties. It is important to carry out basic soil investigation using the right professionals, to ascertain the geological properties or the bearing capacity of the soil, this information will definitely give the type of building to be imposed on such soil. Discouraging quarks is also the best way to mitigate building collapse. Assigning the right jobs to the right professionals is also paramount. For instance, the job of a civil engineer should not be assigned to an architect because they are different professions entirely. Total eradication of substandard materials is absolutely the best to have a durable structure. Building engineers are trained to find solution to problems not to create problems, compromising in construction will absolutely endanger the construction work in a matter of time. Many property owners are also fond of the habit of increasing or adding building loads on existing building properties to maximize their profits. However, for every soil investigation there is a certain building load applicable. The higher the building, the deeper the foundation, Geotechnical properties of the soil will determine the choice and quality of the foundation, in addition, the location (Mainland or Island) should determine the choice of a building foundation.

Conclusion

In this study the predictive accuracy of building collapse casualty in Nigeria was investigated using various machine learning algorithms. The comparative analysis of the performance of five (5) different machine learning algorithms (RLM, SVM, KNN, Random Forest and Decision Tree) was carried out on the building collapse data set of Lagos, Nigeria. The result revealed that the support vector machine (SVM) model has the best performance for predicting the rate of casualty from building collapse in Nigeria. Feature importance inference was also performed using the result of the SVM model, and it was discovered that the building location is the most important variable that determines the building collapse casualty in Nigeria, followed by the height of the building. This study hereby recommends policies that would enhance that proper onsite geo-technical inspection should be done on building site locations before commencement of building constructions in Nigeria.

Disclosure statement

The authors declare that there is no competing interest.

Additional information

Funding

The corresponding author acknowledges the State Research Foundation (FAPESP), Sao Paolo, Brazil for support during this research.

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