ATM Chest Cash Demand Prediction Using Enhanced HistGB Regression Model

T.V. Balakrishnan[1], R Kalaiarasi[2]
[1]Research Scholar, School of Computer Science, Tamil Nadu Open University, Chennai, India
[2]Asst.Professor, School of Computer Science, Tamil Nadu Open University, Chennai, India

Abstract- Automated teller machine, ATM, an efficient fintech invention in catering customer to withdraw money, by not visiting branch. ATM services are expanded to all bank customers and there by each financial institution, in addressing customer service, faces couple of challenges ie (i) availability of cash in the machine for customer access 24X7, as banks cannot load inappropriate cash levels, because of bin size as well as cash usage pattern. Less cash level hit on the customer service and more level hits on investment, thereby revenue earning to bank. Hence, individual ATM cash demand prediction is turned out to be most essential to financial institutions. (ii) tasks of Cash replenishment in ATMs. The cash loading or cash replenishment services are handled by bank staff on demand basis. However, the growth of off-site ATMs, ie the installation of ATMs on the sites of most people gather like Malls, prominent theatres, petrol bunks etc. where in physical security is in built, force the banks to outsource this activity to third party to provide continued customer service by ATMs. Hence it is important to Banks, through any means, to predict the volume of cash requirement, in advance, to replenish in the set of ATMs, so that with minimum transportation efforts, cash filling can be done on the set of ATMs. Information technology comes handy to this prediction. Software based algorithms are more configurable than the statistical application of limited approach of earlier years. This paper explains that the enhanced HistGB regressor algorithm is found out to be suitable for the prediction of volume of cash needs to replenish for set of ATMs to be helpful to banks cash chest or outsourcing contract.

Keywords - ATM, Cash replenishment, Cash in Transit, Optimization, HistGradient Booster, model parameter, hyper tuning.

Introduction

Automated teller machines are mechanization of part of teller role of the banks in dispensing the cash. This machine is equipped with multiple cash bins in which various denomination of cash are loaded for customer access money. Customers are provided with a card, called ATM card which is debit card in nature along with a authentication code in numeric. By inserting the card in the ATM machine in the appropriate slot and key in the right numeric code, PIN, the customer validation is done and for the right access, the customer can keyin the amount of his need. ATM by combination of the software and hardware ensure the right delivery of cash with mixing of various denomination, along with a receipt for the transaction. ATMs are further enhanced with various business functionalities like cash deposit, money transfers, recharging of mobile, payment of utility bills etc by suitable electric money transfers to respective parties. By the nature of its support, ATM turned out to be well receptive initiative of the Financial Institutions. The growth of ATMs turns multi-fold, as Banks, by their service objective of 'self serving' and customer expectation of availability of banking service at the reach, getting satisfied. The cost of transaction is drastically reduced when done at ATM and so all banks issued debit cards to all most all customers and make to migrate to ATM access for cash. There has been tremendous increase in volume of transactions in ATMs, increased customer satisfaction and workload reduction in branch premises.

Cash chest of banks or third-party support (Outsourcing) for cash replenishment (the cash centres) which needs to plan of the cash demand to service the cash-based services of ATMs and through right and secured means transports the cash on a defined time of cash replenishment in ATMs or for the demand by the ATMs. The frequent demand-based service came in to existence, because of inappropriate cash loaded in ATMs. Ie. More cash required by the ATMs may be loaded with less and less is loaded with more. This kind of replenishment leads to multiple expenditures to cash chest, like cash accumulation, transportation for secured methods, ATM downtime for replenishment. Availability of the ATM service has been a special attention among the banking industry and CIT (Cash in transit) company. Factors that cause ATM unavailable are: hardware, receipt, network, and cash, one of the most critical factors is cash availability [14]. Banks loses the customer confidence if cash out results in ATMs. More practical problem in transportation is the time of delivery for cash replenishment, due to road traffic congestion in most cities. These hassles can be avoided by prediction to cash demand of serving all ATMs, by cash centre, so that sufficient cash can be kept for each ATM, as per cash demand of each ATM, at one time under the limitation of ATM cash bin hold capacity. Then bank takes decision of additional ATM in that site, if the cash demand needs multiple times of replenishment. This is elucidated in fig1.

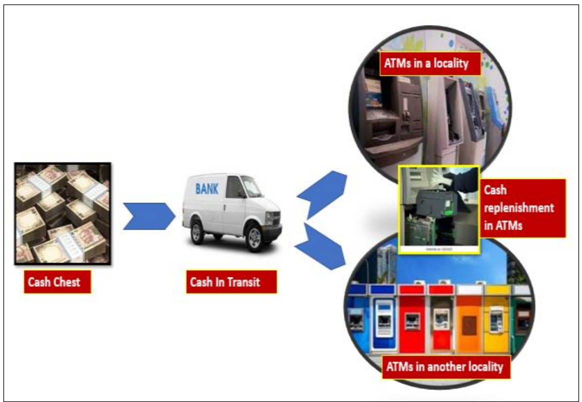

Figure 1 Cash Chest servicing cash replenishment of ATMs (different localities)

Scientific method of forecasting the cash demand of ATMs is possible now, as most effective technology is in place and computation infrastructure is available and cheaper. Hence, prediction of cash demand of cash chest is done with the machine learning algorithm with daily ATMs cash access data. As the prediction of cash demand is the amount (numeric) regression approach is suitable to compute. The datasets of AMTs cash demand are fetched so that the supervised model of machine learning is employed for prediction. The enhanced HistGB regression model is found to be suitable and producing optimizing results.

Literature Review

The ATM cash demand forecasting and ATM cash chest forecasting have been researched sprangly done. From the existing researches and the approaches, there are different factors, implications noticeably banks considered in ATM cash levels as well as the customer services by keeping level of cash at ATM networks. Cash filling by banks, under ATM cash management, primarily to ensure sufficient cash availability, by keeping right amount of 'cash in transit (CIT)'. There are 4 major parties involved ie (i) central regulators (RBI) for whom (ii) banks are responsible in keeping cash availability in ATMs through any means(iii) Cash in transit arrangement with any parties or own, so that (iv) customers can avail services of ATMs 24X7. Banks are keeping the cash level under control, by having multiple limits, like per transaction limit, number of transactions, transaction day limit, cross bank limit etc. Cash management services, especially cash distribution is exercised through hierarchical set up of banks, viz cash centres for each division under territories, in turn under regional or zonal, divisioned by head office[13]. ATM network enables banks to serve with optimum operational cost to address customers expectation, which is acceptable quality of service (turn around time to access cash), however due to socio-economical variants of the population quality cannot be generalized but made suitable differential service qualities defined and established based on categories of people of geographies[20].

ATM Cash demand or level prediction improves the profitability of the banks which enhances the guarantee of stocking money in ATMs and controlling cash availability on Cash in transit on everyday basis[1]. ATMs holding idle money lost its contribution of revenue earning of the bank. Banks, ideally monitor this using the ATM idle cost ratio, which relates the cash deployed vs cash un-utilized on certain period of time. This metric is one of the factors of consideration more efficient cash forecasting algorithms [6]. A right amount of cash availability enhances the banks in cash utilization and also reduces the logistic cost. Logistic cost involves CIT (cash in transit) costs, ie cost involved in replenishing number of times per day, as part of operational cost and due importance to cash idle cost and essential trade off to be done between these costs in alignment to the continuous ATM service and without impacting customer satisfaction[7]. The costs involved for recurring nature for banks, in addition to CIT cost (cash security, transportation & deployment) are maintenance repair cost of ATMs, connectivity link continued establishments. The income from ATMs are estimated in relevance to the cost reduction when serviced at counter and services to other bank customers[22]. ATMs cash filling services includes multiple costs, factored in to probability distribution and mixed integer linear programming, ie cost of cash, uploading and daily services[6].

Considering the ATM cash demand replenishment, done through any forecasting, location of ATM, plays vital role and location for shifting of existing ATM or new ATM installation considers the cost of transportation, count of on-us transactions [19]. ATM cash in transit will have impact in reach of ATMs based on the location and it addresses through various 'shortest path' algorithms to have effective delivery which is similar to identification of location for ATM, that has factors of consideration traffic closer, security, availability of other ATMs, population, commercial organizations mix nearby etc[5]. The ATM cash replenishment has CIT process by which the vehicles' reaching time is one of the factors for non-service during cash out phase. The various factors to be considered for the optimum CIT cost includes length of route, locations of visit, must-visit and may-visit categorization etc[18]. Reducing the number of ATMs by merging of banks ATMs, indirectly increases the operational cost of frequent refilling to the fewer ATMs merged out of many ATMs & services[17].

Cash services in ATMs goes with the denominations available. Having higher denominations in ATM, impacts dispensing of lower cash demands and lower denominations, limits the more dispensing in single transactions. Stock-able amount and denominations are inversely related. Cash services by the ATMs are analysed by banks using various reports such as transaction, daily dispensing and float report[3].

From the inception of ATM installations on site to off site, the ATM cash level maintenance have been a challenge dure to lack of standardized reasonably good scientific method to arrive at the right amount[6], be it for single ATM or set of ATMs through cash chest or cash management centres. More storage of cash, increases the customer happiness as well as decreases CIT cost however cash loses its opportunity to earn. To keep customers, delight and improve cash earning, CIT costs raise. Banks have challenges to have common platform to find out the cost variations on opportunity cost and CIT cost. there are many approaches in forecasting such as regressive AR, auto-regressive ARMA, box-jerkins models like SARIMA (Seasonal ARIMA) and FARIMA (Fractionally ARIMA), neural networks. Neural networks effectively handle well, if only the datasets are complete and consistent[13]. The time series projection has the heteroscedasticity (unequal variance) [7]. As the non-availability of real-world data, the dataset consideration is essential for forecasting ATM or ATM network, as the seasonality and cyclic nature and the exogenous variables. If not treated, results turn sore in time series. VAR-MAX may still fit to the exogenous with due pre-processing and right lose function (SMAPE) [9]. Cash optimization has objectives towards end point of customer delight, achieved by laying effective lesser cost to fetch maximum earnings, those are solutioned through demand management methodologies through cost on hold, order and transport[6]. Operation / Service vertical of management has more researches done, which include designing, customer reach through campaign / call centres / CRM, technology leverage, cash flows, risk spheres etc. however, ATM management researches are less[5].

Cash demand forecasting has been attempted in various years ever since ATMs have been installed and placed for servicing. Various forecasting methods from statistics were employed, especially time series TS. Though, TS has been effective due its less complicative calculation over high ranges of data handling, the dataset-based learning capability is limited to reach perfection [2]. Cash demand prediction of ATMs and cash filling of ATMs service, the solution addressal by linear regression, has customized seasonality parameters, standing static as well as time consuming for parametrization, leading the greater deviation in forecasting[5]. As banks serving the growing mass of customers, the objectives of revenue maximization with resource minimization are equally emphasized. Forecasting of cash demand to individual ATM or set of AMTs are done through various technological methods like KNN, SVM and boasting algorithms based on the feature and structure of transactions data[4]. The forecasting of ATMs cash replenishment could be more effective, when considered, in addition to total cash dispensed, rejected transactions volume.[6]. However, availability of these data / log and accessibility for research, turned out to be challenge.

ATMs enabled with facility of 'cash deposit', these deposited amounts could also be used for dispensing with suitable ATM machine's structure, using due verification / validation of cash notes in deposit. This kind of ATMs are called 'recycling ATM'. However researches on optimization models including deposit amount recycling in cash prediction is not done[6]. The prediction of deposit for future, is yet another problem of its own and also recycling is risky and impact reputation of bank, if the notes are counterfeits. Research deployed Neural Networks by considering the withdrawals & deposits of the ATM as features, by defining larger no of nodes in input (features) and hidden layers[8]. However, ANN handled the previous workloads to forecast in which hidden nodes are populated with summarized efforts, that could not really reflect the discrete pattern of cash demand distribution. Research on ATM cash demand prediction & routes of travel are combined with cash demand through Integer linear programming and routes to reach and fill ATMs, with polynomial time heuristic algorithm carried out with simulation to have optimization and closer results of forecast obtained[7]. Most forecasting studies are towards suitably identifying demand figure, subject to factors of considerations and to reduces error function. Predictions on daily demand focus on the availability of cash which on optimization approaches on cost vs usage will have deviated outcomes, as prediction involves aggregation levels[11]. Researches have been done on the cash demand prediction for individual ATMs, set of ATMs meaning, ATMs adjacent to each there and group ATMs, that are located closer vicinity to each other, using Linear Programming and Dynamic programming with features and cost involvements. Support Vector Machines are useful to regression on the dataset domain and less variance. Problems addressed with SVM, goes better with ANN in forecasting[9] and the LSTM model representing the clustering of time series of groups on each feature will neutralize the bias considerably and yields better results[12].

At the advent of bigdata for big volume of data hold and computation and machine learning algorithms and languages like Python, most insight-able features for ATM withdrawal, such as day, work day, festival day etc. are analysed, identified and used for computation for forecasts [6]. The level of technological services in banking are increasing. Artificial Intelligence, the emerging and growing field of technology, be used in banking usage and forecasting, the best way, on all banking services and interestingly more attention to be paid on Channing Regulatory and Information Technology related laws[23].

The evolving technology-oriented methods in payment domain of banking is encouraging on reliable platform to be used by all cross sections of banking customers. This reduced the operational cost of the banks and retains customer through offering good service satisfaction. Due to the presence of other tech channels like net banking, mobile banking etc and also the low interest rates on cash deployments in markets, bankers need to maintain the ATM network with cash along with other products integration through ATMs[15]. Multiple technological payment channels supported the money transactions of customers, as their easy of usage and payments of internet, mobile complemented to credit cards, ATMs and POS and all service channels posses inverse relation with demand of currency and interest rate, except ATM cards & internet payments[16]. In the study on Financial Inclusion in Nigeria, it is found the technological channels helped to spread banking like ATM networks and revealed that highest transaction volume done are at POS, ATM and other electronic banking channels[21]. Channels for technological banking services are increased so that the physical cash circulation be brought lower levels. The research in Poland, by indicated the non-cash transactions exorbitantly increased over cash transactions in succeeding quarters of year 2020-21[24].

Research Methodology

The research involves the implementation procedure in prediction analysis of cash demands of cash centre, servicing ser of ATMs. The process or farmwork of the research is stated as below fig 2.

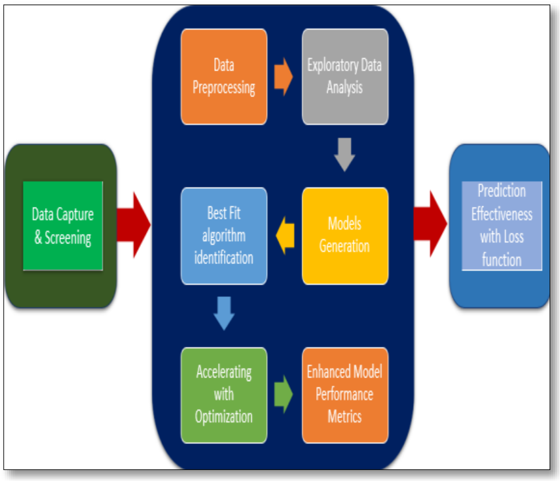

Figure 2 Proposed Research Process in prediction of cash demand for cash chest

The research work done with extensive with ATM transactional data of ATMs which are cash replenished with designated cash chest. The prediction analysis is conducted using the Python language with the help of Jupyter notebook as the platform. It is an open-source web application. It is used by software professionals to manage documents and share varied variety of program code, equations, visualizations and text. The name, Jupyter, comes from the core supported programming languages that it supports: Julia, Python, and R. The Jupyter Notebook is always without Python, as it is common for other languages, to support python, the same is installed. Notably, may distributions of Python is available and the CPython, Python 3 distribution version is used for the conduct of our project.

A cash chest can serve more than one ATM in the locality and hence, the cash in transit should carry effective amount of cash currencies to cash replenish the ATMs. Hence, the data on the cash demand of all the ATMs, are gathered as part of data capture, served by the cash chest on daily basis, from certain ATMs for six years[25]. The datasets are data screened for its quality in terms of null data or missing through data handling tools. The datasets are with transactions involve 10500 records under 12 attributes, as database, considered for research analysis. The datasets contain various essential features, which helps in identifying the cash demand pattern, such as the sequence of working day or holidays, festival or non-festival region, type of ATM, location nature and also from the holiday sequence.

It is important part of any numerical research to have data pre-processing. The designated cash chests are appended to the data in such a way daily data for each cash chest will hall all the features of ATM. The number of ATMs the chest serves is appended to the data. Processability is improvised by converting independent features (ie category values) in to integer type using LabelEncoder. Analysed with various the inter linkages of data and also prepared correlation matrix, to disclose relationships among features.

In order to generate Models for the prediction algorithm effectively, the dataset is segmented 80:20 ratio to training dataset to Testing, post identification of the Total demand amount as the predictor and rest all with features, facilitating to generate model built. Predictor being a numerical, the regression algorithm is employed for analysis. There are more regressor models available and hence, to avoid to be choosily or self-pick, the scientific method to find the each algorithm computation done and evaluating the best out from the model using the regression metrics. The above steps are done using lazypredict.supervised library.

Lazy predict automatically builds several basic ML models using the training data sets, rationally taking statistical approach on the relationships of feature values to predictors. It further evaluates the model effectiveness using regression metrics such as MAE, MSE, RMSE, RSquare, Adjusted R Square. This execution found HistGrandient Booster model as the Best fit algorithm for the existing datasets. The models comparative metrics are shown in Fig3.

Model	Adjusted R-Squared	R-Squared	RMSE
HistGradientBoostingRegressor	0.96	0.96	133831.32
GradientBoostingRegressor	0.96	0.96	134734.05
ExtraTreesRegressor	0.96	0.96	140553.24
RandomForestRegressor	0.96	0.96	141955.23
BaggingRegressor	0.95	0.95	146973.04
HuberRegressor	0.95	0.95	153888.03
LassoLarsIC	0.95	0.95	153894.74
PassiveAggressiveRegressor	0.95	0.95	153982.57
LassoCV	0.95	0.95	154000.57

Figure 3 Top regressor models from lazy predict regression

Accelerating with Optimization

The current HGB algorithm stand effective results. However, the model parameters which are optimized at the algorithm level can not further accelerated with the algorithm. So the model parameter, which are good in degree, to bring the best fit algorithm, is extracted with the objective to further accelerating through Optimization technique. Python offers different methods of optimization such as Bayesian, Random search, Gaussian etc. These optimizations are effectively functional in finding out the target or predict value, especially on the discrete class of designated variables on the predictors[10].

It is analysed that random search optimization will be more appropriate to give closer prediction. The same is used mostly for expensive black-box functions for which any new evaluation requires a lot of computational resources. Random search is actually more practical than grid search because it can be applied even when using a cluster of computers that can fail, and allows the experimenter to change the "resolution" on the fly: adding new trials to the set or ignoring failed trials are both feasible[26].

The random search optimization is expressed as, considering A learning algorithm A is a functional that maps a data set X (train) (a finite set of samples from Gx) to a function f . Very often a learning algorithm produces f through the optimization of a training criterion with respect to a set of parameters θ. However, the learning algorithm has hyper-parameters λ, and the actual learning algorithm is the one obtained after choosing λ, which can be denoted Aλ, and f = Aλ(X (train)) for a training set X (train) . One has to select a regularization penalty C for the training criterion (which controls the margin) and the bandwidth σ of the Gaussian kernel, that is, λ = (C,σ). The need in practice is a way to choose λ so as to minimize generalization error Ex∼Gx [L(x;Aλ(X (train)))]. The computation performed by A itself often involves an inner optimization problem, which is usually iterative and approximate. The problem of identifying a good value for hyper-parameters λ is called the problem of hyper-parameter optimization.

The empirical formula on optimization is

$$\lambda^{(*)} = \operatorname*{argmin}_{\lambda \in \Lambda} \mathbb{E}_{x \sim \mathcal{G}_x}\left[\mathcal{L}\left(x; \mathcal{A}_\lambda\left(\mathcal{X}^{(\text{train})}\right)\right)\right]. \qquad (1)$$

It is difficult to evaluate the expectation over the unknown natural distribution Gx, the value to optimize. With regards to the expectation over Gx, widely used technique of cross validation be employed to estimate it. Cross-validation is the technique of replacing the expectation with a mean over a validation set X (valid) whose elements are drawn x ∼ Gx. Cross-validation is unbiased as long as X (valid) is independent of any data used by Aλ

In Equations 2-4 the hyper-parameter optimization problem as it is addressed in practice:

$$\begin{aligned}
\lambda^{(*)} &\approx \operatorname*{argmin}_{\lambda \in \Lambda} \operatorname*{mean}_{x \in \mathcal{X}^{(\text{valid})}} \mathcal{L}\left(x; \mathcal{A}_\lambda\left(\mathcal{X}^{(\text{train})}\right)\right). && (2)\\
&\equiv \operatorname*{argmin}_{\lambda \in \Lambda} \Psi(\lambda) && (3)\\
&\approx \operatorname*{argmin}_{\lambda \in \{\lambda^{(1)} \ldots \lambda^{(S)}\}} \Psi(\lambda) \equiv \hat{\lambda} && (4)
\end{aligned}$$

Equation 3 expresses the hyper-parameter optimization problem in terms of a hyper-parameter response function, Ψ. Hyper-parameter optimization is the minimization of Ψ(λ) over λ ∈ Λ. This function is sometimes called the response surface in the experiment design literature. Different data sets, tasks, and learning algorithm families give rise to different sets Λ and functions Ψ. Knowing in general very little about the response surface Ψ or the search space Λ, the dominant strategy for finding a good λ is to choose some number (S) of trial points {λ (1) ...λ (S)}, to evaluate Ψ(λ) for each one, and return the λ (i) that worked the best as ˆλ. This strategy is made explicit by Equation 4. The critical step in hyper-parameter optimization is to choose the set of trials {λ (1) ...λ (S)}. Random search as a substitute and baseline that is both reasonably efficient and keeping the advantages of implementation simplicity and reproducibility.

Thus Random search is used as optimization to get prediction closeness using the model parameters of HGM Regressor model. These hyperparameters are in list but more importantly, (i) Learning Rate, (ii) N_estimators, (iii) max_depth, (iv)Min_child_weight.

```
hgbr_regr = HistGradientBoostingRegressor()
param_dist = param_grid = {
    'loss':(['least_squares', 'least_absolute_deviation', 'poisson']),
    'warm_start': (['True', 'False']),
    'learning_rate': loguniform(1e-6, 1),      # Boosting learning rate
    'max_iter': [int(x) for x in np.arange(start = 10, stop = 1000, step = 10)],
    'max_depth': Integer(-1, 256),                         # Maximum tree depth for base learners, <=0 means no limit
    'l2_regularization': loguniform(1e-6, 1e3),      # L2 regularization
    }
tuned_regr = RandomizedSearchCV(hgbr_regr,
                        param_distributions = param_dist,
                        cv = 4,
                        n_iter = 10,
                        scoring = 'neg_mean_absolute_error',
                        verbose = 3,
                        n_jobs = -1,
                        random_state=0)
```

Figure 4 Hyperparameter involved in Random search library

The gain function helps for extending the tree to achieve optimization. This tuned algorithm is called 'Enhanced HistGB Regression Model' This tends to improvise the performance when read through the metrics. The result and discussion section details the enhanced algorithm metrics.

Result And Discussion

The research on the prediction is experimented on the Jupyter platform with required pre-processed ATM daily cash withdrawal transaction data set by aligning to the cash chest of the ATMs, cash replenishment served by the respective cash chest. The best fit algorithm was tracked to be HistGradient Boost Regressor model. This model's best parameters are applied on Random search optimization method to get more effectiveness by tuned HGB regressor model otherwise called Enhance HGB Regression model. The enhanced model is found out be good performance one, when analysed through ERR metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R2 and Adjusted R2.

Metric	HGBRegressor	Enhanced HGBRegressor
MAE	99544.16	98452.34
MSE	17910821880.52	17389444416.00
RMSE	133831.32	131869.04
RMSLE	11.80	11.79
R-Squared	96.0781	96.1923
Adjusted R-Squared	96.0221	96.1379

Figure 5. Tuned Vs Untuned ERR Performance

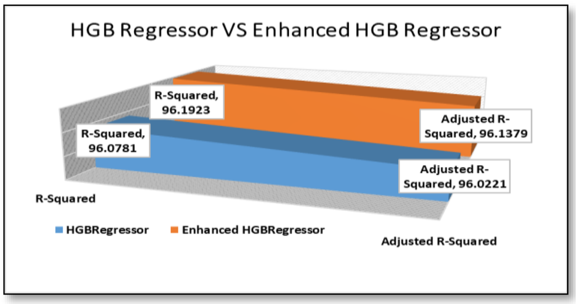

Figure 6 ERR metrics for untuned and tuned HGB Regressor

The enhanced HGB Regressor has good effectiveness which helps cash chest to predict the cash demands of its serving ATMs well in advance and cash flow management will work seamlessly in ATM Replenishment Process. The enhanced HGB regression is tested with the test dataset for prediction and below is the the comparison of original test data vs the prediction.

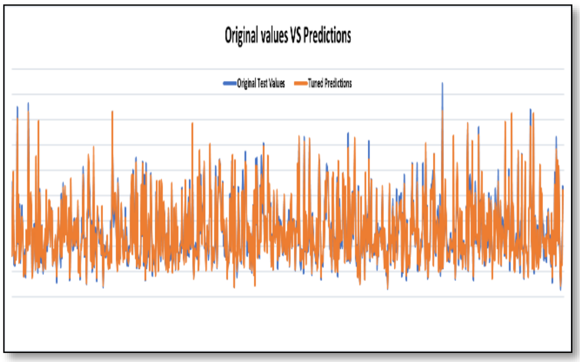

Figure 7 Prediction Vs Original Value comparison

The prediction for the cash chest in cash serving ATMs problem, is well addressed by the enhanced HGB Regressor model. This model shows the best performance metric values such as 96.19% in R-squared and 96.14% in adjusted R-Squared value. This helps to understand the prediction distribution is closer with limited deviation and variance. The analysis of the prediction values are compared with original values to find the suitability of prediction and the loss function. It is found that it showed a lower MAPE Mean Absolution Percentage Error. MAPE is he Mean Absolute Percentage Error (MAPE) can be used to measure the accuracy of a model by finding the loss function that defines the error of a given model. It is mean or average of the sum of absolute differences between the actual and predicted values, divided by the actual value. This is metric that shows out the effectiveness of the loss function. The lower the MAPE the higher the effective prediction and vice versa. However, > 20 is considered to be bad forecasting and between 10 to 20 be Good and < 10 goes very good predict computations[6].

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

M = mean absolute percentage error
n = number of times the summation iteration happens
A_t = actual value
F_t = forecast value

The prediction of existing data coverage (test data) has a lower error percentage ie **< 9%.** ATMs Cash withdrawal are discrete in nature and prediction of demand to a reasonable level accuracy will make the Financial Institutions, in deploying money effective and efficient manner.

Conclusion

Considering the digital banking initiatives of banks, the ATMs growth rapidly across the country. To retain the customer, satisfy the customer expectations and to leverage cost effective but reliable technological solutions, banks ventured more and more ATM implementations and as well as tie ups. The level of cash replenishment of individual ATM is a challenge and because of the spread of ATMs, banks are to keep necessary arrangement to fill the cash in the ATMs. Cash Chest or Cash Centres, in turn to have the right prediction of cash demand on daily basis to put cash in transit for cash replenishments of all ATMs under its service. The research is helpful and it is found that the proposed Enhanced HGB regressor model satisfies the expectation of cash managers in cash chest, in arriving the reasonable prediction of quantum of cash needed for the set to ATMs. More realistic data, with database linkage and all additional features like denominations and distance, population usage etc be added to extend the scope of this research further. Overall, the model performed quite well on training and testing dataset.

Reference

[1] Rimvydas Simutis, Darius Dilijonas, Lidija Bastina, 2008, Cash Demand Forecasting For Atm Using Neural Networks And Support Vector Regression Algorithms, Proceedings Of International On Continuous Optimization And Knowledge-Based Technologies,May 20–23, 2008, Neringa, Lithuania, Pp. 416–421, Isbn 978-9955-28-283-9.

[2] Saad M. Darwish, 2013, A Methodology To Improve Cash Demand Forecasting For Atm Network, International Journal Of Computer And Electrical Engineering, Vol. 5, No. 4, August 2013,Pp.405-409,Doi: 10.7763/Ijcee.2013.V5.741

[3] James Bekker,2011,Atm Cash Management For A South African Retail Bank, Thesis Submitted For Master Of Science In Industrial

Engineering At Stellenbosch University, December 2011.

[4] Evrim Gencalp, Mujde Erol Genevois, Michele Cedolin,2019, Atm Replenishment Forecasting With Support Vector Machine – A Case Study, International Journal Of Industrial Electronics And Electrical Engineering, Issn(P): 2347-6982, Issn(E): 2349-204x, Volume-7, Issue-10, Oct.-2019

[5] M. Erol Genevois, D. Celik, H. Z. Ulukan,2015, Atm Location Problem And Cash Management In Automated Teller Machines, World Academy Of Science, Engineering And Technology International Journal Of Industrial And Manufacturing Engineering, Vol:9, No:7, 2015, Waset.Org/Publication/10002685.

[6] Bilir C. & Doseyen A. (2018), Optimization Of Atm And Branch Cash Operations Using An Integrated Cash Requirement Forecasting And Cash Optimization Model, Bmij, (2018), Vol.6, Iss.1, Pp. 237-255 Doi: Http://Dx.Doi.Org/10.15295/Bmij.V6i1.219

[7] Seyma Batı, Didem Gözüpek,(2019), Joint Optimization Of Cash Management And Routing For New-Generation Automated Teller Machine Networks, Ieee Transactions On Systems, Man, And Cybernetics: Systems, Vol. 49, No. 12, December 2019,Pp. 2724-2738,

[8] Sefik Ilkin Serengil, Alper Ozpinar, 2019, Atm Cash Flow Prediction And Replenishment Optimization With Ann, International Journal Of Engineering Research And Development Umagd, (January 2019),Doi: 10.29137/Umagd.484670,Vol.11,Iss.1,Pp. 402-408

[9] Muhammad Rafi, Mohammad Taha Wahaby, Muhammad Bilal Khanz, Hani Razax,(2020), Atm Cash Prediction Using Time Series Approach, International Conference On Computing, Mathematics And Engineering Technologies – Icomet 2020

[10] Zareapoor, M., Seeja, K.R. And Alam, M.A. (2012) Analysis Of Credit Card Fraud Detection Techniques: Based On Certain Design Criteria. International Journal Of Computer Applications , Vol. 52, Pp.35-42. Doi Https://Doi.Org/10.5120/8184-1538

[11] Yeliz Ekinci, Nicoleta Serban, Ekrem Duman, (2019), Optimal Atm Replenishment Policies Under Demand Uncertainty, Springer-Verlag Gmbh Germany, Part Of Springer Nature 2019, Https://Doi.Org/10.1007/S12351-019-00466-4

[12] Varsha Vishwakarma , Hylish James , Richard K Bururu , Jaideep Matto,(2020), Atm Cash Replenishment With Clustering Series, International Journal Of Scientific & Engineering Research Volume 11, Issue 5, May-2020, Issn 2229-5518 Pp8-11

[13]Kazbek Dadteev, Boris Shchukin, Sergey Nemeshaev, (2019), Artificial Intelligence Technologies To Predict Cash Flow, Open Access Article In Procedia Computer Science, Www.Elsevier.Com/Locate/Procedia1877-0509

[14]Tazkiyah Herdi, Ardiansyah Dores,(2020), Improving Cash Availability Of Atm Using Lean Replenishment Pull For Sharia Bank In Indonesia, Manajemen Bisnis, P-Issn: 2089-0176 E-Issn: 2655-2523 , Vol. 10 No. 02 October 2020 Page 78-88 Doi: 10.22219/Mb.V10i2.13317

[15] García Cabello, J. (2020). Money Leaks In Banking Atm's Cash-Management Systems, Virtual Economics, Vol.3, Iss.2, Pp. 25-42. Https://Doi.Org/10.34021/Ve.2020.03.02(2).

[16] Janak Raj, Indranil Bhattacharyya, Samir Ranjan Behera, Joice John And Bhimappa Arjun Talwar, Modelling And Forecasting Currency Demand In India: A Heterodox Approach, Reserve Bank Of India Occasional Papers, Vol. 41, No. 1: 2020

[17]Liekem.Vanderheidea,Leandroc.Coelhoa,Irisf.A .Visa,Roelg.Vananholtb,(2019), Replenishment And Denomination Mix Of Automated Teller Machines With Dynamic Forecast Demands, Computers And Operations Research, Https://Doi.Org/10.1016/J.Cor.2019.104828.

[18]Andrea Chiussia, Christos Orlisb, Roberto Robertib, Wout Dullaertb,(2020),Atm Cash Replenishment Under Varying Population Coverage Requirements, ,Journal Of The Operational Research Society, Https://Doi.Org/10.1080/01605682.2020.1866443

[19]Abdolhussein Shakibayinia, Faraz Forootan , (2018), Presenting A Model For Identifying The Best Location Of Melli Bank Atms By

Combining Clustering Algorithms And Particle Optimization, International Journal Of Computer Applications Technology And Research, Issn:-2319–8656, Vol. 7, Iss. 1, Pp.12-18.
[20]N Raghu Kisore , B Koteswaraiah, (2016), Improving Atm Coverage Area Using Density Based Clustering Algorithm And Voronoi Diagrams, Elsevier Information Sciences, Pp. 1–20, Http://Dx.Doi.Org/ 10.1016/J.Ins.2016.09.058
[21]Clement Chiahemba Ajekwe. (2020), Assessment Of Efforts At Expanding Financial Inclusion In Nigeria. International Journal Of Economics, Finance And Management Sciences. Special Issue: Financial Inclusion And Challenges Ahead. Vol. 8, No. 5, 2020, Pp. 180-187. Doi: 10.11648/J.Ijefm.20200805.12
[22]Mujde Erol Genevois, Derya Celik, H. Ziya Ulukan,(2015), Analytic Network Process Approach For Automatic Teller Machines Deployment Problem, Presented At The 6th IESM Conference, Seville, Spain, October 2015
[23]F. Königstorfer And S. Thalmann, (2020), Applications Of Artificial Intelligence In Commercial Banks – A Research Agenda For Behavioral Finance. Journal Of Behavioral And Experimental Finance, Doi: Https://Doi.Org/10.1016/J.Jbef.2020.100352.
[24]Jerzy Witold Wiśniewski, (2021), Forecasts Of Non-Cash Turnover In Poland, Xv International Scientific Conference On Analysis Of International Relations, Methods And Models Of Regional Development, Katowice, Poland 22-23 June 2021
[25] Data Set From Www.Kaggle.Com
[26]James Bergstra , Yoshua Bengio,(2012), Random Search for Hyper-Parameter Optimization, Journal of Machine Learning Research, Vol. 13 (2012), pp.281-305