ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Real estate web scraping with EDA

[1] N.Harish, [2] M.Sampath, [3] L.Saicharan, [4]M.Karthik, [5]Mr. S . UPENDAR,

[1,2,3,4] U.G.Scholor, Department of ECE, Sri Indu College Of Engineering & Technology, Ibrahimpatnam, Hyderabad.

[5]Assistant Professor, Department of ECE, Sri Indu College Of Engineering & Technology, Ibrahimpatnam, Hyderabad.

ABSTRACT

Country's economic status can derived from many complex and branched indicators, one of which is property prices estimation. Working on such indicator changed the state of literature from many perspectives and corners. Whilst the scarcityofsuchworksimposesaneedforit,anddemonstrates an unutilized aspect of the economy that requires little resourcestocreatesomebusinessandacademicopportunities. In this work, efforts evolved to address the problem of estimatingproperties prices accurately, in specificapartment's pricesamongTheAmmanCity,TheCapitalofTheHashemite Kingdom ofJordan. Leading to shed the lights on employing data science different techniques namely data processing, analysis andpredictivemodelingfor adopting and estimating theapartment'sprices basedonadvertisementdata published through the web and its extracted location geocodes. In addition,theworkevaluatesthefinalanalysisreportedresults basedonselectedevaluationmeasures,andcomparethemwith other five similar works on such problem conducted in other countries.Tryingtoaimtoenrich the literature with valuable insights gained using Machine Learning and Data Mining different predictive techniques mainly, and its related conditions, branches and requirements for other data processing and analysis techniques under the data science umbrella.

Key words: Deep Learning, Machine Learning, Predictive Modeling, Property Prices Analysis Prediction.

1. INTRODUCTION

Propertyprices;a greatindicationofa country's economic status. It gives an indication of the economic wellbeing and stability, and being considered a clear manifestation of inflationamongstothereconomicphenomena[1].Usually,this field observed to be either the original sin and/or the most prominent presentation of most economic events, and it considered being so complex and branched sector.

Most of economy aspects can be defined or described in termsofpropertysector,asitisincombinationwithfoodareof theoldestsectorstohaveemergedincorrespondencetosheer demand imposed by the basic needs for survival for modern humans[2].Thoughotherspeciesdohave,housingneedsthat are not necessarily simple as represented with the case of beavers,andtheirwell-engineereddams.Rather,humanstook it several steps ahead, and delegated the housing and construction to form the earliest jobs and occupations of builders. In addition, it further expanded with economic evolutionwithfurtherbranchingandbreakingdownofroles to includemostofearlyoccupationsandindustries.Forinstance, dominating engineering until the early days of the industrial revolutionexpandedtospanover other sectors and industries beside construction, which did not stop the propertyindustry frombeingamajorplayerintheeconomicsceneuntilnow[3]. Furthermore,itdisplayeditsdominancewith theemergenceof economies of scale, banking economies and loan based economiestoagreatdegreeasshownbythefinancialcrisisin 2008[4].Beingofthisimportance;i.e.propertyindustry,lead to trigger a lot of work on the topic as demonstrated by the plethora of scientific works and publications in the field. Leading to form a solid base of literature around the topic especially in the financial aspect [5]. Such an example and original motivation behind this work is the property price prediction,havingsetitselfwiththeirisdataset related work as thedefault examples ofthetrendyand important field ofdata science.

Inthisview,andduetotheinterestingattributesofthe property problem. Alongside, how it corresponds to the interrelations and different macroeconomic components [6]. Furthermore, the rich nature of data involved in house price estimation and prediction, and thesemi obvious nature ofthe factors involved of property prices, and the existence of previousmoretraditionalmethodsfortheestimationprocess [7];all makes for a great use case for studies, serving both businessrelatedstudiesandacademicapplications.Becauseit leadrelatedpartiestorevealsthehiddenaspectsofacountry's economy,whilstalsodemonstratingclearlytheeffectsofdata scienceandpredictiveanalysisanddatamanipulation

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Table1: SimilarWorksSummaries

Inputs				Results		
Dataset	**Dataset Dimensions**	**Used Models**	**Data Splits**	**Model**	**Evaluation Criteria**	**Value**
UCI's Dataset (HousingValueofBoston Suburb)	452 X 13	SVM(1),LSSVM(2),PLS(3)	400-52	(1)	**MSE**	**10.7373**
					R. Time	**0.4610s**
				(2)	**MSE**	**20.3730**
					R. Time	**20.3730s**
				(3)	**MSE**	**25.0540**
					R. Time	**0.7460s**
LocalDatainSpain	1187 X 6	MLP[1HiddenLayer]	952-237	MLP	**R2**	**0. 8605**
					RMSE	**39540.36**
					MAE	**28551.34**
"Zillow.com", "magicbricks.com"	21,000 X 15	LinearRegression(1),Multivariate Regression (2), Polynomial Regression(3)	80% - 20%	(1)	**RMSE**	**1.201918**
				(2)	**RMSE**	**16,545,470**
				(3)	**RMSE**	**11359157**
bProperty.com	3505 X 15	GB-Regression(1),RandomForest (2),SVMEnsemble(3)	80% - 20%	All	**RMSE**	**0.1864to0.2340**
randomsamplefrom www.bluebook.co.nz	200 X 7	MLP	80% - 20%	MLP	**R2**	**0.6907 to 0.9**
					RMSE	**449,111.46to 1, 014,721.92**

techniques duetothestraightforwardness ofthe problem and the size of the available work on it [8]. Starting with the benefitsyieldedofanaccurateestimationforpropertybuyers, alongsidetheassumptionrelatedtoifacertainpropertypriced fairly, and tohavea better idea about the possible impacts of each of the attributes on the price and in what way. All are leading to facilitate the process of making a purchase decisionandbudgetandprioritiessetting forthem. In addition, helpingthepropertyinvestorsinknowingifapurchasedealis abargainwithahighmarginofprofitornot.Ontheotherside ofthe same transaction type for describing the property sales process,wehavepropertysellersandpotentialinvestorsinthe propertysectorwhethertheyareindividualsorcorporatesized parties. Who are looking forward to understand the market prices,andhowmuchtheyexpecttochargefortheirproperties, andwhataspectsrelatedtothemarket in ordertoconcentrate on, and what to dismiss, all are a common use case for data science some techniques.

The contributions of the work presented in here are threefold: (1) demonstrates utilizing data science to figure more countries' economic aspects, which requires huge resourcestocreatesomebusinessandacademicopportunities andinsights. (2)Presenting a comparativepredictivemodeling and analysis studyfor Jordanian propertymarket against five similar works conducted in different countries. (3) Finally, reporting theanalysis resulted insights upon adopting different machinelearning techniques and evaluation measures for the presented problem.

The rest of the work organized as follows. In section 2, presentingsimilarworksforothercountriesandtheirreported results.Section3providesthemethodologyadoptedtoconduct end-to-enddatapreprocessingandExplanatoryDataAnalysis (EDA) considering real estate apartments prices prediction basedonadvertisementdataandlocationsgeocodes.Section4 provides the predictive modeling analysis different experiments conducted using machinelearning. In Section 5, the work provides the reported results alongside the needed discussions,beforeconcludingthepresentedworkinsection6 and its future next steps.

2. SIMILARWORK

Asaheavilycoveredtopicespeciallyintherecentyears,the optionstocomparetoandbenefitfromareplenty. Hence, we chose a sample of few papers that addressed the price estimation problem that felt closest and most relevant to this work.

Starting with hedonic regression, where we performed severalregressiontoeachattributeindividually.Then,tryingto observethechangeinatargetattribute(Price),soconstructing the final equation of the predicted variable of the weighted estimation attributes. With an origin out of the real estate, pricing [9] and some interesting use cases [10]. A lot of literature on this problem is studying the alternative methods fortheestimationwitha concentrationonthe useofmachine learning. Table.1 summarizes five works followed with a discussion for each further more in this comparative work. Inthefirstwork[11],usingaUCIdatasetwithhousingprices data in Boston, and 13 attributes in the data with a relatively low number ofinstanceat 452. Authors presented their work ascomparisonofthreedifferentmodels;namelyPartialLeast Squares (PLS) regression, Support Vector Machine (SVM), andLeast-SquaresSupport-VectorMachine(LSSVM),where the third is somewhat a kernelled version of regular SVMs with an optimization included by design. The results shows that SVMs where superior to the other two methods both on Mean Squared Error (MSE) and fitting time of the model, thoughLSSVMwouldhavesmallerfittingtimeifthe

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Table2: WebScrapedData Attributes

Attributes	Type	Attributes...	Type...	Attributes...	Type...	Attributes...	Type...
ID	INT	AdImagesCount	INT	AirConditioning	BIN	NearbyFacilities	BIN
Title	STR	City	STR	Heating	BIN	Security	BIN
Date	STR	Location	STR	Balcony	BIN	Built-inWardrobes	BIN
RealEstate	BIN	No. Rooms	INT	Elevator	BIN	SwimmingPool	BIN
PaidAdFeature.1	BIN	No. Bath Rooms	INT	Garden	BIN	SolarPanels	BIN
PaidAdFeature.2	BIN	Area	INT	GarageParking	BIN	DoublepaneWindows	BIN
PaidAdFeature.3	BIN	Floor	INT	MaidRoom	BIN	AdPost	STR
PaidAdFeature.4	BIN	Age	STR	LaundryRoom	BIN		
Price	INT	PaymentType	STR	IsFurnished	BIN		

parameteroptimizationweredropped,whileallmodelsseems to yield acceptable results.

Thenextworkpresentedin[12]providesagoodoutlookon theSpanishrealestatemarket.Itutilizesdatathatspansovera long time interval by making use of a one hidden layerMulti-LayerPerceptron(MLP),inordertoyieldanestimation model of the real estate price based on some exogenous variables.Authors claimingthesuperiorityofone hidden layer over two, where the results obtained are to some degree a supporteroftheclaim. However, furtherexamination ofsuch workshouldtested, considering thevarious architectures and parameters that an MLP could take. While also taking into account the benefits of the two hidden layers models [13] beyond the general function approximation abilities that artificialneuralnetworkshave[14].withasomewhatrichdata on verticallywith 1187 instance the data is slim horizontally with only6 attributes, demonstrating with the calculated R2, RMSE and Median Absolute Error (MAE) the potential Artificial Neural Networks (ANNs) have for solving such problems and improvement over traditional hedonic models whichisanobservationthatissharedbetweenagoodfraction ofliterature.

Comingmoreon thetechnical side. Authors in [15] makes use of rich data with 21000 instances and 15 attributes and triesseveralregressionmodels,namelylinear,multivariateand polynomialregression.However,theevaluationmethod leaves alottobedesired,going with RMSE solelyleaves a need for dataexplorationtounderstandtheresultsfurthermore.Butthe useofsuch evaluation criterion could beunderstandabledueto thenatureoftheexperimentwheremostregressionmodelsrely on minimizing some sort of error or residual to produce the model and with the iterative nature of the tuning both the models and the data.

Consideringtheensembleway,authorsin[16]basedonthe assumptionthatseveralmodelsshouldyieldbetterresults.As intheaggregatedresultsofseveralmodelsshouldpresentmore supporttoacertaindecision.Thisworkutilizesseveral models that has shown good results, exceeding the performance of other models that do not utilize the ensemble paradigm like ANNs. With 3505 instances in the data set and 19 attributes, the dataset considered is features rich and should allow for better estimation. As it reduces, the complexity of the fitted modelduetothehigherdimensionalitythatisatthesametime mighthinderthefittingandlearningprocess duetothelarger search space for the solution. The results is good yet could benefit from a clearer presentation of the results, this while lacking in clarity demonstrated the potential benefit of ensemblemethods forthis typeofregression.In addition, the data preprocessing and transformation effect on the regression's final output, and this with therespect tothedata categoriesandhoweachmighteffectonthelearningprocessin terms of model and training/fitting performance, while elaborative on the effects of tuning machine-learning ensembles with parameters such as depth and number of estimators [17].

Followinginthetrendofneuralmodelsforpriceestimation, whilegoingfurtherwiththehedonicversusANNhouseprice estimation. Where they share a similar definition of the problemaddressedtosolve.Authorsin[18]dives deeperinto both the hedonic and artificial neural network theories. Alongside the histories and the inflection of the aforementionedtheoriesonthecorrespondingmodels.Rather, scarce in the data used with 200 instances and 7 attributes. Nevertheless,themodelsproducedvarieshighlyinprediction performance. That is rather obvious in terms of R-squared, whichit clearlyexplained in thedifferent architectures ofthe usedneuralmodels interms ofnumberofneurons. However, the scarcity of data raises some questions regarding the top obtained performance, that explained by the more complex model producing it. In addition, the number of test instance indicateslesssupportfortheresults. Nonetheless thestatistical nature of this work and the emphasis on the hedonic-neural comparison and attributes contribution. The analysis conductedgivesanindication,thattheseresultsarejust

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

indicative of the statistical conclusions of a potential superiorityfortheneuralmodelsoverhedonicones,inthereal estatepriceregressiondemonstratedwiththeuseofmeasures like White Heteroscedasticity Test and confidence intervals. While also showing that, even aggregated features may lose some information, but are still a feasible option if fitting performance is of an issue [19]. An interesting observation herewouldthedifferentcontributionstoeachattributeandits importance level for the regression in the two models presenting the low interpretability of them in terms of their producedmodelrepresentedbypatternsseenindatatoproduce the regression or classification shall not always comply with the higher level semantics observed by humans [20].

Mostofliteratureincludingthediscussedexamplesaboveuse an 80% and 20% for the training and test data splits. In addition, the most addressed the hedonic regression as a common method for such a problem and use case. while also describingitasthemethod tobereplaced bymachinelearning, duetoitsmoredynamicandcomplexnature[21],[22].Which allow capturing more intricate trends and adapting more throughtimerelyingononlinemachinelearningmethods [23]. In the meantime, facilitating the time based adaptation and thereforeperformingbetterforeconomicanalysis [24],either presenting data over a temporal axis implicitly or explicitly, whichwillaccommodated bysome machine learning models in later stages of analysis. For instance, Hidden Markov Models (HMMs) and Recurrent Neural Networks (RNNs) [25],withsomefutureanticipatedandcurrentlydemonstrated cases of image based price estimations [26]. As much other type of estimators in different areas that rely on machine learning [41]-[43].

3. JORDANIAN MARKET: REAL ESTATE APARTMENTS PRICES PREDICTION

Methodology

Startingfromacquiringthedatafromonlinesourcesasnodata is available for the Jordanian real estatemarket, as most data with these specs mostly aggregated from many sources. For instance, adopting web-scraping approach. Then, this work proceeds to dealing with data issues, though the actual workflowwasmoreiterativethansequentialitwilllistedlatter for convenience. After handling the data work, this work continues to the predictive modelling. Where, several experiments conducted using several models, namely Linear andGradientBoostingforsimpleandcomplexregression-based models. Support Vector Machines and RandomForests,whicharebothensemblesandrelyontheuse ofdecisiontrees[27],[28],astheirweakermodelstobuildthe ensembles. Finally, MLP as advanced predictive modeling technique. Each of the aforementioned predictive modeling techniques has its own unique features and their fitting use cases. Finally, these models are then fitted with the prepared data after manipulation then tuned if necessary to yield acceptable results.

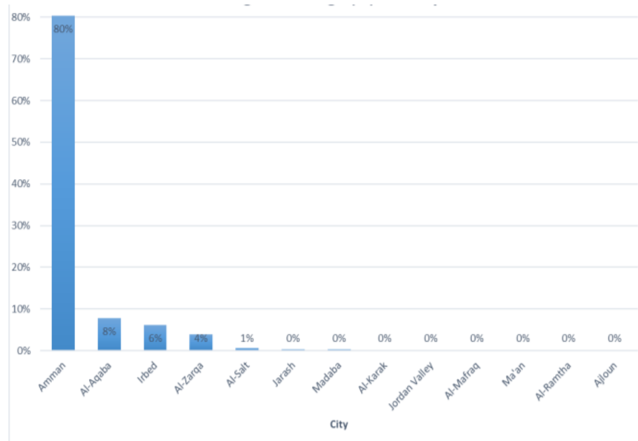

Figure1: AdvertisingPercentage(%)perCity.

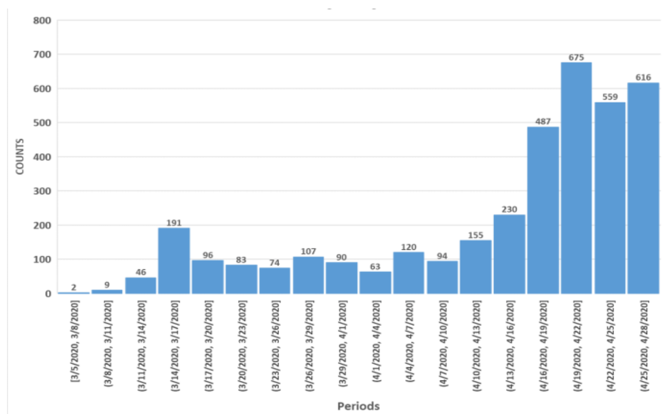

Figure2: No.ofAdvertisementsListedperAdvertisements'Dates.

DataAttributes

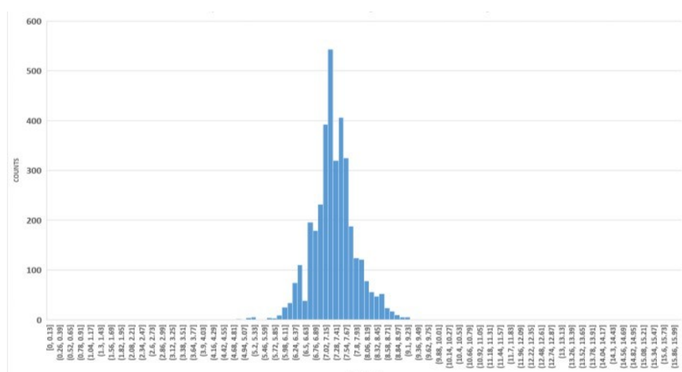

Figure3: ApartmentAreainM^2–TheWholeData(Beforeapplying splitting and outlier's removal).

The work analysis dataset obtained from an online sales websitesthatincludelistingsforapartmentforsalesinJordan, which is the categorythis work is going to use. The original data contained 3697 instances with 34 attributes ranging in type and benefit to the apartment price estimation process. Severalmanipulationcarriedover thedatain-ordertoreacha

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

statewheremodels areabletocapturethetrend in the data in order to produce a sane estimation. Then, exploring the data visually to understand the nature of the data, also it is a necessary for some preprocessing steps, for instance, discovering outliers in order to remove and the data distribution tobetterunderstand theresults obtained from each model. Rather, the visualization for the data can provide valuableinsights about the Jordanian real estate market from withthevisualaidsastheycansubstituteevenpartiallyforthe moredefinedmetricsoftheinteractionsbetweentheattributes of the data [29] including price.

As mentioned earlier, the obtained data set contains 34 attributes, and usage to those attributes that listed in Table.2 can varies to conduct different types of analysis other than estimating real estate prices. However, the data instances collected are for advertisements related to apartments in specificinoverallJordanforashortperiod(5,March2020to 28, April 2020).

Data Cleaning

Someessentialstepsaretobedonebeforeanyfurtherprocess should take place to accommodate for the tools to be used natureandtoreducethebiasanderrorsthatmaybeperceived in the final outcomes of the data whether it being predictive models or simple statistics. Such steps varies from dropping NULLs in the main anticipated features to dealing with inconsistentvalues,duplicatesandobviousnoise.Inaddition, to fix data types, correcting, and unifying the values of attributes as the data collected from online sources that are open for contribution from any seller and non-seller parties, whowantstomakeanapartmentlisting.duetothefairnumber ofinstancesinthedata,andtheassumingthatthedistribution andcoverageofthedataistobepreservedduetosizea lot of messy and unclean data were dropped, that will also be contributingtothespeedofthefittingandlearningprocessfor the predictive modelling part.

Data Preprocessing

Keepinginmindthatthedatashouldbetooclean and perfect inordertoleaveroomforthemodels togeneralizeoverunseen data. Several preprocessing steps done, each serving some purpose,overlappingwithpreprocessingsometransformations applied to the features serving purposes.

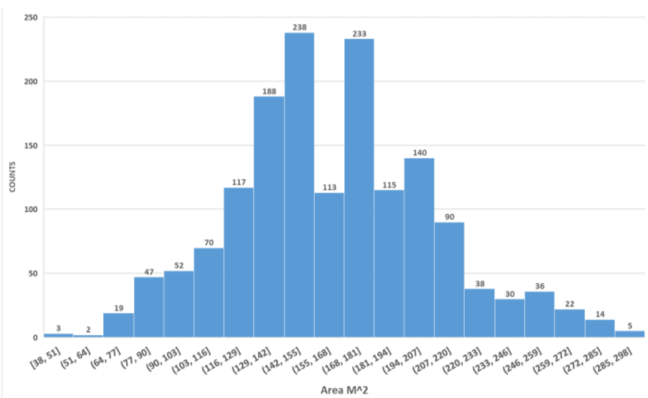

Figure4: ApartmentAreainM^2–TheTrainingDataSplit(After applying outlier's removal).

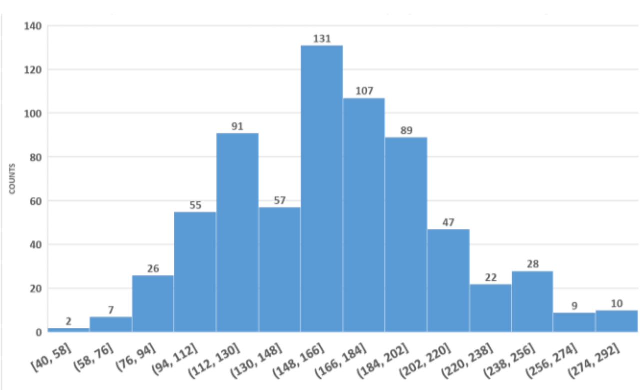

Figure5: ApartmentAreainM^2–TheTestDataSplit(After applyingoutlier'sremoval).

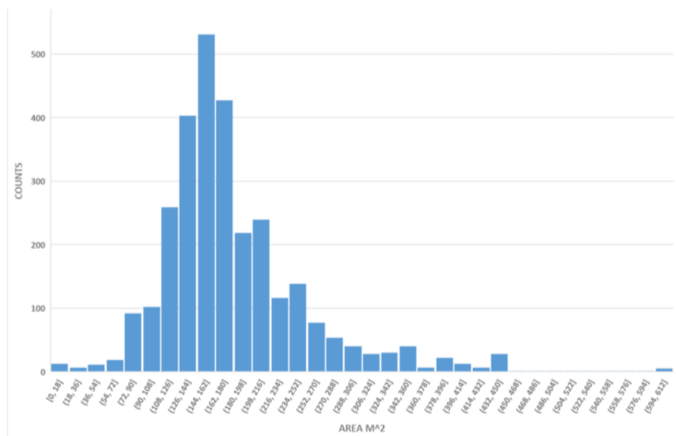

Figure6: AverageofListedApartments'AreainM^2

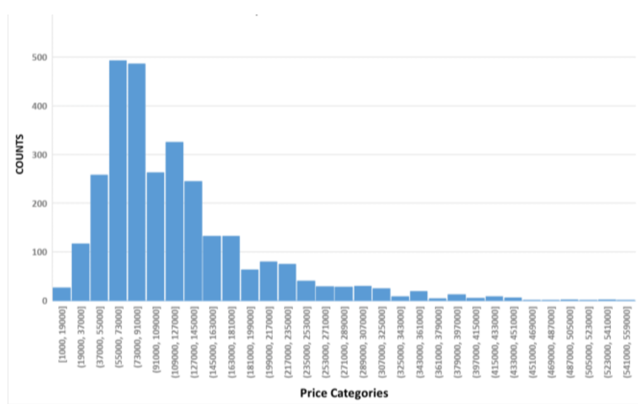

Figure7: ApartmentsPricesDistribution

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

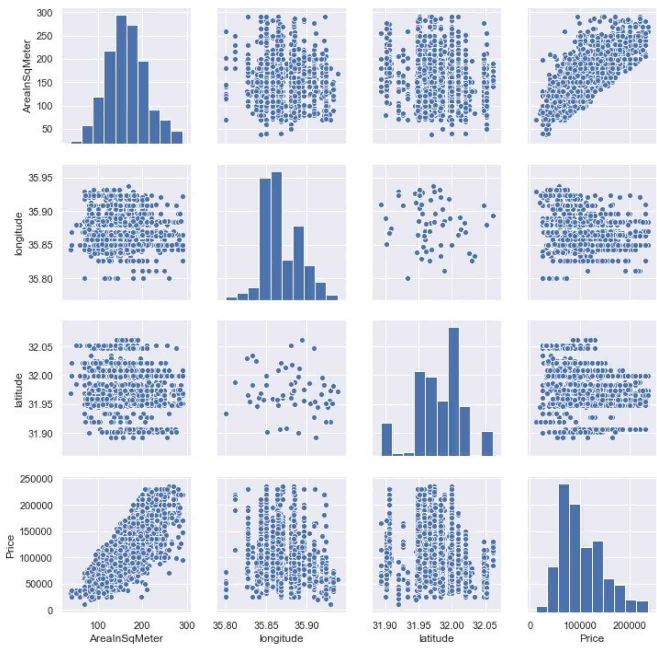

Figure8: PriceandAreaRegressionRelationship.

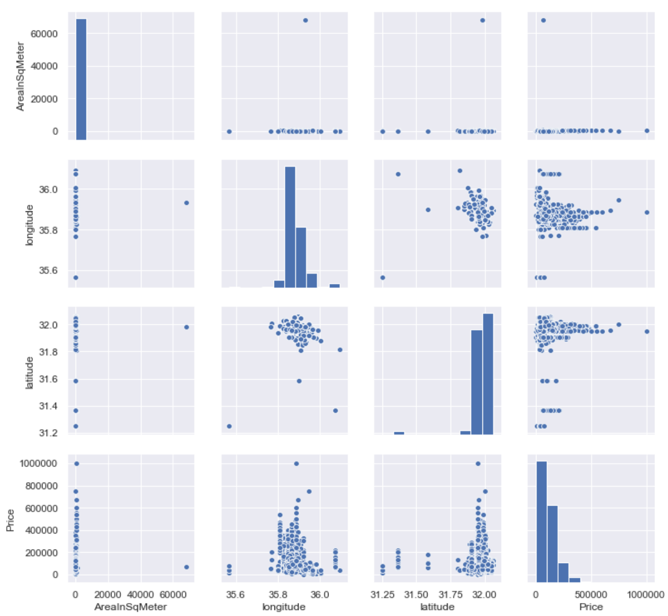

Figure9: DiscoveringOutliersusingtheCorrelationMatrix.

Thoughnotusedinestimatingprices,thisattributeyields some insights about the listings when coupled with other attributes indicating what makes a listing stays for long without it ever sold. For instance, Figure.6 shows the number of advertisements listed per day for the data collection period. Such result would communicate some indicators for economists about when such market movement for demands and offers may appear during the differentseasonsthestudyandregulates[30].Suchattribute transformed from its described form as a categorical and a datevariabletoa continuous variablerepresentingthedays sincethelistingwasposted,asimilartransformationwas

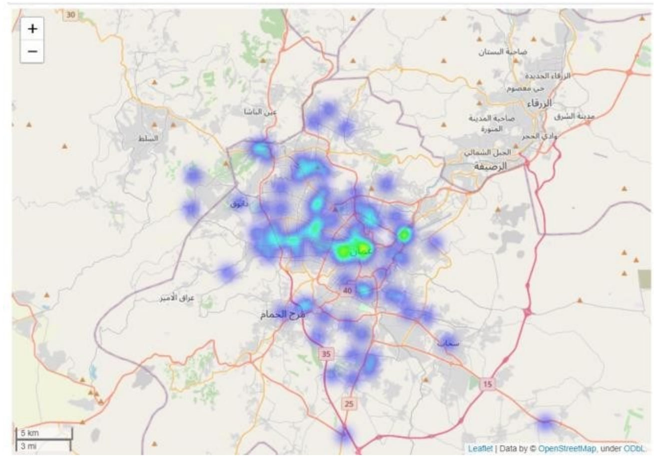

Figure10: GraphicalHeatMapsbeforeOutliersRemoval.

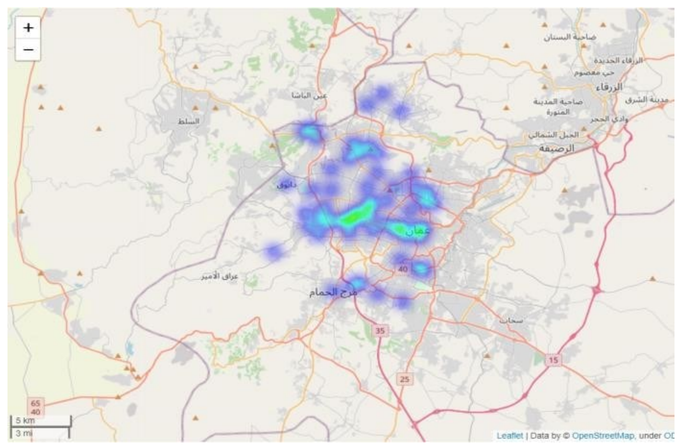

Figure11: GraphicalHeatMapsbeforeOutliersRemoval.

Table3: RegressionModelsReportedModel-BasedScoreResults

Trail	DatasetType	ModelsGenerated	Results	
			Train	Test
Linear Regression	RegularData, ScaledData	1	0.67	0.71
EnsembleMethod–GB-Regression	RegularData,ScaledData	1	0.97	0.81

Table4: RandomForestBestEstimatorSearchingTechniques

Trail	Dataset Type	Results	
		Train	Test
RF-Standard	Regular	0.92	0.82
RF-Randomized Search	Regular	0.92	0.8
ThreeTypesUsed:Standard[12],Grid[16],andRandomized[17]			

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

Table5:SVMReportedResults

Trail	Dataset Type	Results	
		Train	**Test**
SVM	Regular	-0.05	-0.04
SVM-Normalized(y)	Scaled	0.9	0.800.72
SVM-RandomizedSearch	Scaled	0.84	0.77

applied tothe Building age attribute although on a smaller interval.

- **Creating Price per Meter Attribute:** To be able to fairly judgethelistingsforfurtherstepslikeoutlierremoval,price and area might not be enough as in the case of large apartment with a matching price tag and a small apartment with a higher than actual value price.
- **Binary Attributes Creation:** Dealing with attributes that stillincludecategoricalvaluesisnotidealespeciallyforthe mostlycontinuous and numericimplementations ofmachine learningmodels.So,andinordertofacilitatetheuseofsuch attributes (Is Furnished and Payment Type). Each were transformed into two attributes that each can take 0 or 1 allowingfor4permutationsandpreservingtheothervalues oftheattributeslikethe'notspecified'or'both',whilealso beingeasiertouseincomputingprocessesduetoitsnumeric nature.
- **Data Splits:**Thedatadividedwitharatioof70\% to30\% fortrainingandtestsetsrespectively;thisdonebeforefurther processing and exploring data to reduce bias in the fitting andlearningprocesses,hence,avoidskewingtheprediction results.Thesplittingprocessresultedwiththe2044records for training dataset and 877 records for test dataset considering the aforementioned preprocessing steps.
- **OutlierRemovalUsingQuartiles:**Outliers removedoutof necessitybased on thedistribution observed bythe Figures 3-5.Thismighthinderthe performance of some machine

Table6:MLPReportedResults

Modeling MechanismUsed	**Models Generated**	**Results**	
		Train	**Test**
L-BFGS (1HiddenLayer9 Neurons)	1	0.76	0.71
ADAM (1HiddenLayer 100 Neurons)	1	0.71	0.71
L-BFGS (1HiddenLayer 120 Neurons)	40	0.76	0.7
ADAM (1HiddenLayer 10-200Neurons)	20	0.66	0.67
ADAM (2HiddenLayers 10-200X10-200 Neurons)	134	0.93	0.67

learningmodels,outliersweredetectedandremovedusing5 attributes (Price ,Area ,Price Per Meter, Longitude And Latitude)usingtheInterquartileRuleforOutliers,whilethe z-score method didn't yield as good results.

The resulting dataset after the preprocessing is smaller in size (2253 X 26) and uniform in distribution (Train: 1572 X 26, Test: 681 X 26), though the data is still noisy, the early predictive models fitting results indicate an enhancement in comparison to fits that conducted after. The other attributes dropped since not relevancy to the prices predictive analysis conducted. Alongside this type of trimming using quartiles, anothertypeoftrimmingusing z-scorewereexperimented and yields a less satisfactory results. I.e. it does not solve the outlier'sproblembecauseonlyonerecordtrimmedwhenusing Areainsquaremeterfeature.Therefore,westickwithquartiles method.

Table7: EvaluationMeasures

Measure	**Usage**	**BestValue**	**WorstValue**
R-squared(R2)	Represents proportion of variance of y thatexplainedbyindependentattributes inthemodel.Whichindicatestrengthand goodnessoffitofthedatatothe regressionline.	100%, the model explain all the variabilityof the response data around the mean.	LowerandNegativeValues, i.e. themodelexplainnothingabout the response data variability around the mean.
MeanSquared Error (MSE) [38]	Riskmetric based onthe expected value of thesquared error or loss.	Lower values as there would beexcellentmatchbetweenthe actual and predicted dataset.	Higher values in addition to the lower values with no excellent matchingbetweentheactualand the predicted dataset.
Median AbsoluteErro r(MdAE) [39]	1. Outliersrobust(unaffectedbyvaluesat the tails). 2. Errororlossfunction. 3. Calculateunivariatevariability.	Lower values as there would beexcellentmatchbetweenthe actual and predicted dataset.	Higher values in addition to the lower values with no excellent matchingbetweentheactualand the predicted dataset.
MeanAbsolute Error (MeAE) [40]	1. Riskmetric. 2. Scale-DependentAccuracyMeasure.	Lower values as there would beexcellent match between theactualandpredicted dataset.	Higher values in addition to the lower values with no excellent matching betweentheactualand thepredicteddataset.

Table8: ExperimentalEnvironment HWSpecifications

Item	Description
PCType	Laptop
Brand	ASUSROGG703GXNotebook
CPU	Inteli9-8950HK
RAM	64GB
HD	3x1TBNVMeSSDRAID
GPU	NVIDIAGeForceRTX20808GB
Screen	17.3"FHD144Hz3msG-Sync
OS	Windows10Pro

VisualizationandEDA

The main difficultyin here is not coming up with ideas to testandevaluateonthedataset;itiscomingupwithideasthat arelikelytoturnintoinsights and valuableindicators about the trends and patterns hidden in the data [31]. In specific, those related tothepropertybusiness. Accordingly, we have to ask questionsthatleadtodeepunderstandingfortheobservations collected from the online different sources. Therefore, implementingtheconceptofExplanatoryDataAnalysis[29], whichisagraphicalanalysistechnique,thatemploysavariety of techniques in order to maximize insights, uncover the underlying patterns, important features extraction; detect anomalies and outliers, and further determining the optimal tuned model settings.

Adopting EDA mechanism for discovering normal distributions for the attributes, or finding the relationships between the attributes of different types, namely categorical and/orcontinuous,willbetterleadtofindvaluableinsights in thedata.Forinstance,theaverageareainsquaremeterforthe listed apartments in Amman city was around 150 M2 as appears in Figure.6. Whereas the average prices for the apartments appear to be around 74,647$ as appears in Figure.7.

Fromanotherperspectivemostlyrelatedtooutliersdetection

Table10:MLPModels'AverageEvaluationScores

DataSplitUsed	**ADAM … (1)**	**L-BFGS … (1)**
R2-Train	0.895829998	0.763841224
R2-Test	0.674536562	0.705861926
MSE-Train	203345745.1	460995310.1
MSE-Test	662487173.3	598723783.7
MeAE-Train	6596.689703	12485.69136
MeAE-Test	14093.88889	14651.50066
MdAE-Train	9198.765418	16161.98873
MdAE-Test	18868.66751	18622.71286
Adam=(∑Score)=155;L-BFGS=(∑Score)=41…(1)		

4. PREDICTIVEMODELLINGEXPERIMENTS

ScalingtheAttributes

Non-binary attributes were scaled using z-score normalization to reduce variance and reduce peak values effectsbyreducingspreadallowingsomemodelstofitthedata better [32]. The predictor variable, the price in this case was also scaled to account for the use of distance in SVMs [33], using the z-score normalization as well, as was discovered through the experiments.

LearningModelsEmployedandExperimentsSetup

Severaltypesofmachinelearningmodelsusedand employedinthecomparativeprocess,whilsttheyall implementedandevaluatedaccordingtoSCIKITLearn Package [34] provided functionalitiesonthe basisof scaled dataandregulardata,wherethelatetypemeans noscalingor transformationonthedatasetsusedbeforelearningprocesses. Firstly, one ofthe simplest machine learning models used in addition,evaluatedinthisworkwasLinearRegression,which better suited for linear data, as the degree of the regressor is limited to one. It implemented under several assumptions as thementioneddatalinearity,independenceandseveralothers,

Table9:MLPTop-10R2-RankedModels

MLPID	**MLPsolver**	**Layers Structure**		**R2**		**MSE**		**MdAE**		**MeAE**	
#	**Solver**	**Layer1**	**Layer2**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
168	LBFGS	7	0	0.74	0.7	510320333	603349036	13284.7	14313.1	17158.3	18909.7
155	LBFGS	6	0	0.74	0.72	512527565	571225948	13098.8	14093.8	16984	18154.8
135	LBFGS	5	0	0.74	0.72	515600513	576319329	13741.5	15218.9	17261.6	18609.6
136	LBFGS	5	0	0.73	0.72	521154916	574018441	13071.1	14527.5	17213.6	18367.5
85	ADAM	180	0	0.73	0.73	522058827	554305503	13099.4	13982.5	17178.6	17895.2
87	ADAM	190	0	0.73	0.72	530135262	563064858	12943.2	13909.9	17294.4	17992.9
92	ADAM	200	0	0.73	0.72	530948320	561928876	13009.8	13994.8	17334.2	17987.2
81	ADAM	160	0	0.73	0.72	535067377	572433080	13245.1	14357.1	17425.3	18199.8
75	ADAM	130	0	0.73	0.72	535396669	564242215	13326.5	14501.8	17366.4	18064.9
79	ADAM	150	0	0.73	0.72	536741651	568369222	13220.1	14319.3	17422.7	18132.1

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

is usually expressed as minimizing error/residual or some transformationofit,tobemoreprecisethelinearregressionin thiscasewheremultipleexplanatoryvariableexist itis called multiplelinearregression[35].NextEnsemblelearningbased method–GradientBoostingRegression (GB-Regression) [27] analysisconductedonthefeaturessets interms oftheregular data and the scaled data. The configurations for such model include400estimatortrees withnumberoffive levels for the maxdepthandminimumtwosamplesrequiredtosplitanode atlearningrate0.1withloss function tobeoptimized namely leastsquaresregression.Theresultsyieldoverfittedmodelin acceptable range according to the standard score function included in the model implementation, whilst higher results when considering R2 (R-Squared) that is coefficient of determination provided by the same learning model implementation [34]. However, used regression models' alongside the standard model-based evaluation [36] scores yielded on the scaled data where summarized in the Table.3.

Another Ensemble learning based method employed with almostthesamenumberofestimatorssetbeforefor GB-RegressionisRandomForest[37].Theanalysisconducted onthefeaturessetsintermsoftheregular data,yieldedworst results interms ofmodeloverfittingfor training data with no anysignificancechangesinthepredictionresultsbasedonthe standard model score function, the results reported in Figure.12.

Furthermore, investigations following acquiring the overfittingresultsfromtheprevioustrail,leadininitiatingtwo search processes to figure out the best configurations for the decisiontree,i.e.whatarethebestattributesorparametersfor the Random Forest method to better fit the data and create a good price estimator on unseen data. Total 450 runs for the differentconfigurationsprovidedthatcoulddividedintothree similar runs of each configuration based on a different data split(fold).Thereportedresultsshowminorimprovementover the almost default model, and this can be judged due to the theory of the ensemble methods that several models shall be better than one. To provide more convenience, the results acquired upon using such learning methodology depicted clearly inTable.4usingthestandardmodel-basedevaluation

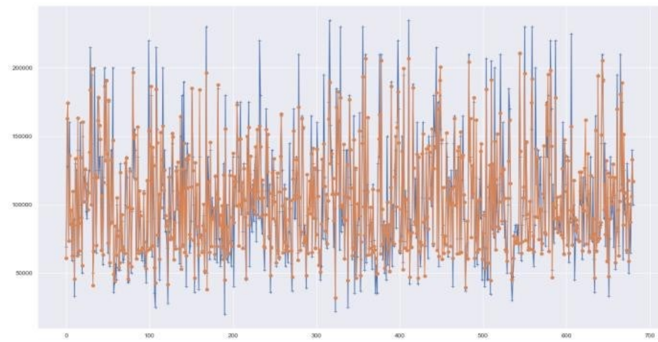

Figure12: RandomForest500EstimatorsOverfitting[Training: 0.96,Test:0.82].

scoredresults.

Thebestestimatorconfigurations[34]foundedforRandom Forest model were 1500 estimators with max depth 100 and minimum sample leaves of 2 and 6 minimum samples splits evaluated using the criterion MSE[38].

On the other hand, Non-linear SVMs [33] to aim to fit a morecomplexand non-linearlyseparabledata using theRBF Kernel conducted on the features sets in terms of the regular and scaled data. Results yielded bad results with no any significancechangesinthepredictionresultstoovercomethe previous trails and models for the regular data, whilst it indicated that SVMs perform better with the scaled data as it uses distances, so a drastic difference in distances will cloud the finer trends in the classifier (or used regression model). Experimentsshowstheoverfittingishigh duetothedifference fortheR2scorebetweenthetrainingandthetestdatasets,yet its acceptable range for the model. Leading the work to continueitswaytowardexhaustivefiguringoutthe best-optimized model's hyper parameters. Nevertheless, the reported results show minor improvement over the almost default scaled model (overfitting went down, hence better resultsforthemodel.i.e.moregeneralizedmodel).Theresults reportedbasedonthestandardR2scorefunctionforthisstage in the Table.5.

Table11: OtherModels'EvaluationScores

ModelType	**R2**		**MSE**		**MdAE**		**MeAE**	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
LinearRegression	0.67	0.71	637955720.47	587972332.82	15565.15	15893.58	19509.84	19227.21
GB-Regression	0.98	0.82	43477365.96	371593383.38	2510.74	9485.87	4220.98	13674.42
SVM	0.90	0.72	0.10	0.30	0.01	0.30	0.16	0.39
SVM–Best Estimator	0.84	0.77	0.16	0.24	0.12	0.28	0.25	0.36
RandomForest	0.97	0.82	67627086.20	360681397.17	3925.50	9529.00	5671.71	13455.18
RandomForest – BestEstimator	0.92	0.82	146483386.29	367440117.15	5719.66	9973.90	8415.14	13727.93

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

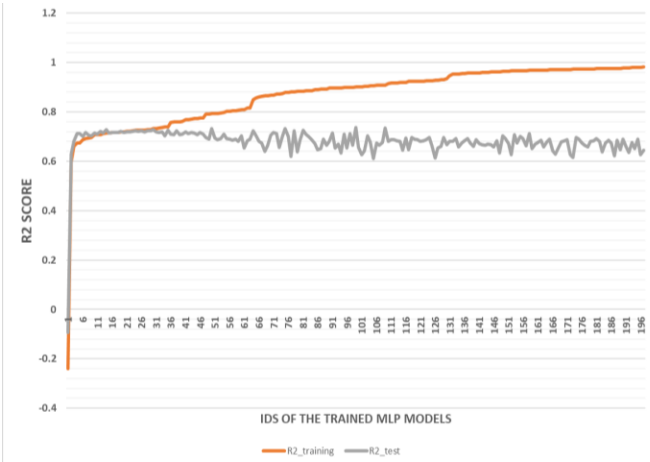

Figure13:MLPEvaluatedModelsUsingR2.

Finally,thisworkcontinuoustothemostcomplexlearning methods. Usually an MLP or a neural model should exceed other models in performance. Given that, if it tuned well, a processthatishighincost,and could beinfeasibleconsidering thewaysimplermodels cangivesatisfactoryresults forsome problems.Here we triedtwo types of solvers (ADAM andL-BFGS), each is different in degree and where it excels. However, the most complicated parameter to tune is the architecturesize,duetoitbeingnotasingleparameterandthe highdynamicityofit.Thatwasaddressedbyfittingaround196 MLPsdifferentinarchitectureandsolverswhilestickingwith mostlydefault parameters except for theactivation where we went with the ReLU as we're not constrained in computing powertoadegreethatweshouldtrysomethingsimplerasthe ReLU provides the flexibilityin activation and scaling. Each model where allowed to go up to 100000 epochs while constrained with the tolerance over the enhancement in loss overavalidationsplitof20\%ofthetrainingdata.Exhaustive trails and stochastic optimizations applied to the learning models, whilst each got an ID and exported to external serializable files for further analysis, evaluation and future usage, for instance Figure.13. For convenience, all the used MLP models' standard model-based evaluation [34] scores yielded on the scaled data where summarized in the Table.6.

ExperientialMachineUsed

All the analysis early mentioned and the results for all experiments conducted on machine that got the hardware specifications as depicted in Table.8.

5. RESULTSANDDISCUSSIONS

PredictiveModelingEvaluationCriteria

Fittingtimedismissedhereas apparent bytheexperiments of the MLP and the grid search optimization for the SVM and RandomForest.WhiletheR-squaredwasthemainevaluation criterion through the experiments. Other common regression evaluation metrics added later on like mean squared error, medianabsoluteerrorandmeanabsoluteerror.Moreover, sinceallthetrained and tested models backed-up on external files,providingthechancetotrydifferentevaluationmeasures, and assessing the conduction of the final models evaluation and selection for both training and testing datasets. For instance,measuresdepictedinTable.7arethechosen criteria to amend this comparative work with the evaluation results needed.

PredictiveModelingEvaluation

Consideringtheevaluationcriteriashownearlyin this work, inhere,listingfortheevaluationresultswilltakeplace,where it will be organized in showing the MLP results first and the best evaluated architectures followed by the discussions related, then the rest of the models and the best accuracy achieved.

Starting with MLPtrained and tested models. The resulted evaluationscoresshowninTable.9depictthatL-BFGSsolvers outperformswellovertheAdamsolversintermsofoverfitting on smaller datasets as all of them ranked in terms of R2 evaluation measurefor thetop ten thetrained and thetwisted MLP models for both solvers.

The best achieved results for the MLP models that got the highlightedarchitectureswhereallhaveonelayerwith number ofneuronslessthanorequalto180neurons for thefirst. One hundredsixtyninedifferentmodels trained on longer periods measured in hours, all evaluated and the best accuracy achieved in terms ofR2 measurewas (0.72) for both training andtestdatasets.FurtherresultsshownbytheMSEmeasures thatdepicttraininggotlossscoregreaterthantestscorewitha littledifferenceonunseendata,yetstill acceptableresults for the models. Another interested result for MLP models evaluated related to the MdAE and MeAE measures that appeared to measure the well fit considering the MdAE's robustnessfortheoutliers,andthisproofthecorrectnessofthe methodologyadopted in this work for removing the outliers. Whilst the Table.10 shows the average results for each evaluation,measureusedfordifferentMLPsolversamongthe trained and tested models. It appears clearly that L-BFGs solvers performwellon smaller datasets while Adam solvers sufferfromlearningoverfittingforsuch typeofdatasets. Other models shown in Table.11, where Random Forest ensemble method, which used for conducting complicated predictive analysis for the given data. Evaluation results using standard scorefunctionforrandomforesttrainedandtestedmodelson regular data basis, i.e. data not transformed or scaled, shows clear overfitting which listed early in this work early in Figure.12. The initiated two search strategies, grid and random,wheregridsearchusedtotestconfigurationsonlower searchingrates,whichthensupplementrandomsearchforthe sakeoffiguringout best configurations for therandom forest algorithm.Thisprocessresultedinnumberofestimators1500 ofmaxdepthof100;errorfunctionMSEforminimumsamples splitandleafsofsix,andtworespectivelyasallthebestprices estimatorconfigurations.Eventheprimaryevaluationresults showsminorimprovementoverthedefaultmodel,buttheR2 remainedshowinghigherdeviation(i.e.Overfitting)achieved as MLP modeling techniques used for random configuration lookup. These results can attributed to either low instances searched and/or the efficiencyof the default models to begin with on smaller dataset.

Finally, Linear and GB-Regression evaluated well using R2 scorefunctionwithasmallindicationforminortrendymodel overfitting. Whilst the non-linear SVMs using RBF Kernel yielded in two very different standard model score-based results,givinganindicationthatSVMsperformbetterwiththe scaled data as it uses distances, so a drastic difference in distances will cloud the finer trends in the classifier (or used regression model). Rather, best estimator configurations founded shows minor improvement over the default model evenreportingwithR2evaluationmetric,whichshowsbetter results in the other models employed.

6. CONCLUSION

Not all the previously mentioned aspects and benefits to work on such problem changed the state of literature and the work on the Jordanian market. Whilst the scarcity of such works imposes a need for it, and demonstrates an unutilized aspect of the economy that requires little resources to create some business and academic opportunities. In addition, helping in further understanding of Jordanian economy, and potentially diagnosing some problems and recommending actions to be taking to revert the declination ofthat economy and identifywhere correction should be concentrated. Going further to cover all the potential inductions and recommendations amongst other possible extractions and solutions to this problem start with methodological data science's use case. The use case shown is offering a comparative study of several predictive and descriptive methodsoveranonlinecollecteddataofapartmentsforsalein Jordanandtheirprices alongsidelistedfeatures.Thefocus of the work concentrate mainly on data mining and machine learning different techniques. Some anecdotal insights were listed that relates to the apartments market and on the techniques used in this work, where the experimental results might indicate some relations, the consolidation of the observedinterrelationsstillneedsamorethoroughstudywith more comprehensive tests on bigger datasets. However, the work focuses on exploring someoftheattributes interactions while preparing them for the predictive modelling, and reshaping, transforming and filtering the data for a better learning by addressing some of basic data problems like distribution, outliers and incompatible attribute types with somemodels.Thenandbasedonaselectedsubsetofmachine learning models that vary in complexity and behavior fitted withwhiletuningboththemodelsanddatainatrialtoenhance performance, judging based on several criteria (R2, MSE, MdAE,andMeAE)andtryingtoexplainand evaluatethefinal resultsobtained.Thenextstepsforthisworkwillgodeeply insidethelocaland/orglobalmarketsdifferentareas,tryingto provide insights about, enrich, and curate the local and/or global economic aspects, which had better enhance the understanding and aid specialists to draw insightful conclusions about the market different indicators using different data science techniques

REFERENCES

1. M. Hoesli, C. Lizieri, and B. MacGregor. **The inflation hedging characteristics of US and UK investments: a multi-factorerrorcorrectionapproach**.TheJournalof Real Estate Finance and Economics, 36(2), 183-206. 2008. https://doi.org/10.1007/s11146-007-9062-6
2. S. J. A. P. Zavei, and M. M. Jusan. **Exploring housing attributes selection based on Maslow's hierarchy of needs.** Procedia-Social and Behavioral Sciences, 42, 311-319. 2012.
3. S.Hudson-Wilson,F.J.Fabozzi,andJ.N.Gordon,.**Why realestate?**.TheJournalofPortfolioManagement, 29(5), 12-25. 2003.
4. J. Aizenman, and Y. Jinjarak. **Real estate valuation, current account and credit growth patterns, before and after the 2008–9 crisis.** Journal of International Money and Finance, 48, 249-270. 2014.
5. A.Anari,andJ.Kolari.**HousePricesandInflationReal Estate Economics**, 30(1), 67–84. 2002.
6. K. E. Case, E. L. Glaeser, and J. A. Parker. **Real estate andthemacroeconomy.**BrookingsPapersonEconomic Activity, 2000(2), 119-162. 2000.
7. S.B.Billings.**Hedonicamenityvaluationandhousing renovations**.RealEstateEconomics,43(3),652-682. 2015. https://doi.org/10.1111/1540-6229.12093
8. N. Shinde, and K. Gawande. **Survey on predicting property price.** In 2018 International Conference on Automation and Computational Engineering (ICACE) (pp. 1-7). IEEE. October 2018.
9. B. Sopranzetti, **Hedonic Regression Models.** pp. 2119–2134 10 1007 978–1–4614–7750–1 78.)
10. D. Harrison Jr, and D. L. Rubinfeld. **Hedonic housing prices and the demand for clean air**. 1978.
11. J.Mu,F.Wu,andA.Zhang.**Housing value forecasting based on machine learning methods**. In Abstract and Applied Analysis (Vol. 2014). Hindawi. January 2014.
12. J.M. N. Tabales, J. M. Caridad, and F. J.R. Carmona, F. J. R. **Artificial neural networks for predicting real estate price.** Revista de Métodos Cuantitativos para la Economía y la Empresa, 15, 29-44. 2013.
13. E.D.Sontag.**Feedbackstabilizationusing two-hidden-layer nets.** In 1991 American Control Conference (pp. 815-820). IEEE. June 1991.
14. Y.Li,andY.Yuan.**Convergence analysis of two-layer neural networks with relu activation.** In Advances in neural information processing systems (pp. 597-607). 2017.

15. R. Manjula, S. Jain, S. Srivastava, and P. R. Kher. **Real estate value prediction using multivariate regression models.**InIOPConferenceSeries:MaterialsScienceand Engineering (Vol. 263, p. 042098). November 2017.
16. A.A.Neloy,H.S.Haque,andM.M.UlIslam.**Ensemble learningbasedrentalapartmentpriceprediction modelbycategoricalfeaturesfactoring**.InProceedings ofthe201911thInternationalConferenceonMachine Learning and Computing (pp. 350-356). February2019. https://doi.org/10.1145/3318299.3318377
17. A. Singh, and R. Lakshmiganthan. **Impact of different datatypesonclassifierperformanceofrandomforest, naive bayes, and k-nearest neighbors algorithms**. 2018.
18. V. Limsombunchai. **House price prediction: hedonic price model vs. artificial neural network.** In New Zealand agricultural and resource economics society conference (pp. 25-26). June 2004.
19. G. J. McKee, and D. Miljkovic. **Data Aggregation and Information Loss** (No. 381-2016-22080). 2007.
20. H. YILDIRIM. **Property Value Assessment Using Artificial Neural Networks, Hedonic Regression and Nearest Neighbors Regression Methods.** Selçuk Üniversitesi Mühendislik, Bilim ve Teknoloji Dergisi, 7(2), 387-404. 2019.
21. M. Miyamoto, and H. Tsubaki. **Measuring technology and pricing differences in the digital still camera industry using improved hedonic price estimation**. Behaviormetrika, 28(2), 111-152. 2001.
22. H. Xu, and F. Mueller. **Work-in-progress: Making machinelearningreal-timepredictable.**IEEE Real-Time Systems Symposium (RTSS) (pp. 157-160). IEEE. December 2018.
23. N. H. Abroyan, andR. G. Hakobyan. **A review ofthe usageofmachinelearninginreal-timesystems.** BulletinoftheNationalPolytechnicUniversityof Armenia.InformationTechnology,Electronics,Radio Engineering, (1), 46-54. 2016. https://doi.org/10.22606/fsp.2017.12002
24. R.Bellazzi,C.Larizza,P.Magni,S.Montani,andG.De Nicolao. **Intelligent analysis of clinical time series by combining structural filtering and temporal abstractions.**InJointEuropeanConferenceonArtificial Intelligence in Medicine and Medical Decision Making (pp. 261-270). Springer, Berlin, Heidelberg. June 1999.
25. X. Chen, L. Wei, and J. Xu. **House price prediction using LSTM**. arXiv preprint arXiv:1709.08432. 2017.
26. E. Ahmed, and M. Moustafa. **House price estimation from visual and textual features**. arXiv preprint arXiv:1609.08399. 2016.
27. F.Zhang,B.Du,andL.Zhang.**Sceneclassificationviaa gradient boosting random convolutional network framework.** IEEE Transactions on Geoscience and Remote Sensing, 54(3), 1793-1802. 2015.
28. L. Breiman. **Using iterated bagging to debias regressions.** Machine Learning, 45(3), 261-277. 2001.
29. M.F.DeOliveira, and H. Levkowitz. **From visual data exploration to visual data mining: A survey.** IEEE transactionsonvisualizationandcomputergraphics,9(3), 378-394. 2003.
30. S. Lima, A. M. Gonçalves, and M. Costa. **Timeseries forecasting using Holt-Winters exponential smoothing:Anapplicationtoeconomicdata.**InAIP Conference Proceedings (Vol. 2186,No.1,p.090003). AIP Publishing LLC. December 2019. https://doi.org/10.1063/1.5137999
31. C. Lee, O. Kwon, M. Kim, and D. Kwon. **Early identification of emerging technologies: A machine learning approach using multiple patent indicators**. Technological Forecasting and Social Change, 127,291-303. 2018.
32. R. Berwick. **An Idiot's guide to Support vector machines(SVMs).**RetrievedonOctober,21,2011.2003.
33. A. Abanda, U. Mori, and J. A. Lozano. **A review on distance based time series classification.** Data Mining and Knowledge Discovery, 33(2), 378-412. 2019.
34. F.Pedregosa,G.Varoquaux,A.Gramfort,V.Michel,B. Thirion, O. Grisel, ... and J. Vanderplas. **Scikit-learn: Machine learning in Python.** The Journal of machine Learning Research, 12, 2825-2830. 2011.
35. R. A. Bottenberg, and J. H. Ward. **Applied multiple linear regression** (Vol. 63, No. 6). 6570th Personnel Research Laboratory, Aerospace Medical Division, Air Force Systems Command, Lackland Air Force Base. 1963.
36. E.W.Steyerberg,A.J.Vickers,N.R.Cook,T.Gerds,M. Gonen, N. Obuchowski,... and M.W. Kattan. **Assessing the performance of prediction models: a framework forsometraditionalandnovelmeasures**.Epidemiology (Cambridge, Mass.), 21(1), 128. 2010.
37. L. Breiman. **Random Forests**. Machine learning, 45(1), 5–32. 2001.
38. N.J.Nagelkerke.**A note on a general definition of the coefficientofdetermination**.Biometrika,78(3), 691-692. 1991.
39. Z.Wang,andA.C.Bovik.**Meansquarederror:Loveit or leave it? A new look at signal fidelity measures**. IEEE signal processing magazine, 26(1), 98-117. 2009.
40. C.J.WillmottandK.Matsuura.**Advantagesofthemean absoluteerror(MAE)overtherootmeansquare error (RMSE) in assessing average model performance**. Climate research, 30(1), 79-82. 2005.
41. R. Tripathi, and D. P. Rai. **Comparative Study of Software Cost Estimation Technique.** International Journal ofAdvanced Research in Computer Science and Software Engineering, 6(1). 2016.
42. V.Kale,andF.Momin.**VideoDataMiningFramework for Surveillance Video.** International Journal of AdvancedTrendsinComputerScienceandEngineering, 2(3).2013.
43. A. A. Mahule, and A. J. Agrawal. **Hybrid Method for Improving Accuracy of Crop-Type Detection using Machine Learning**. International Journal, 9(2). 2020.

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

https://doi.org/10.30534/ijatcse/2020/209922020

44. M.Akour,O.AlQasem,H.Alsghaier,andK. Al-Radaideh. The effectiveness of using deep learning algorithms in predicting daily activities. International Journal, 8(5). 2019.