the model shows 66.05% of relative absolute error, 92.84% of root relative squared error is produced by K =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. If n-neighbors =5, the model shows 66.82% of relative absolute error, 88.39% of root relative squared error is produced by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model.. If n-neighbors =7, the model shows 67.88% of relative absolute error, 87.63% of root relative squared error is produced by K =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model.. If n-neighbors =9, the model shows 68.18% of relative absolute error, 86.89% of root relative squared error is produced by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model.

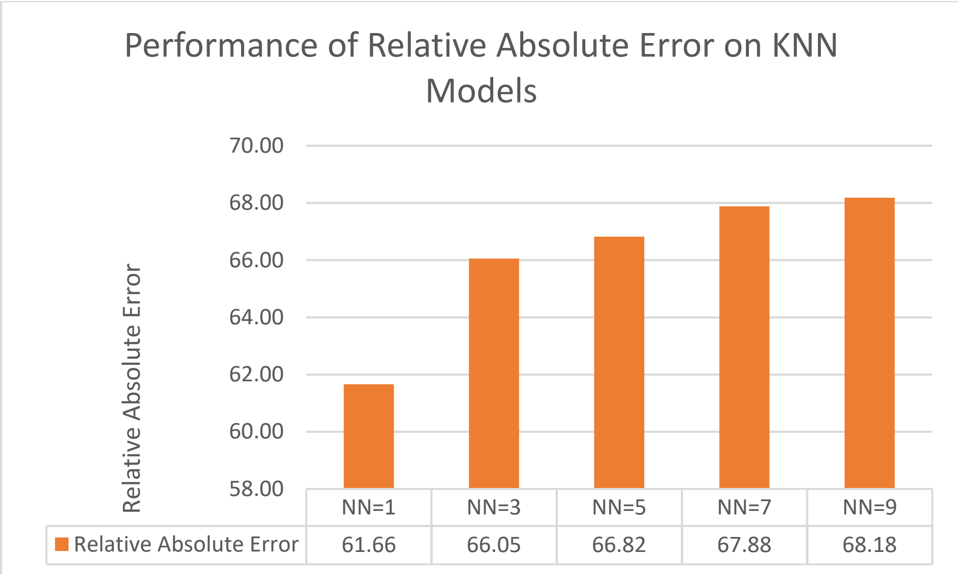

Figure 13: Relative Absolute Error performance of KNN Models

The above picture 13 shows that the measurements of relative absolute error value on KNN models by applying various n-neighbors with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The smallest relative absolute error performance is 61.66 %which is hold by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The highest relative absolute error performance is 68.18% which is hold by n-neighbors =9 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. Rest of the n-neighbors =3 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, and n-neighbors =7 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model are holing 66.05% of relative absolute error value, 66.82% of relative absolute error value and 67.88% of relative absolute error value respectively.

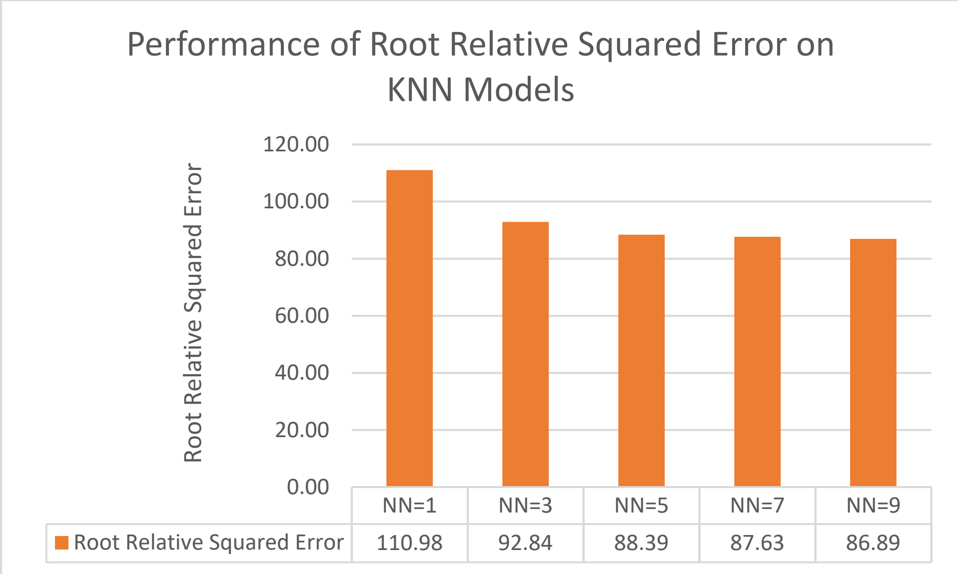

Figure 14: Root Relative Squared Error performance of KNN Models

The above picture 14 shows that the measurements of root relative squared error value on KNN models by applying various n-neighbors with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The largest root relative squared error performance is 110.98 %which is hold by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The smallest root relative squared error performance is 86.89% which is hold by n-neighbors =9 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. Rest of the n-neighbors =3 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, and n-neighbors =7 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model are holing 92.84% of root relative squared error value, 88.39% of root relative squared error value and 86.89% of root relative squared error value respectively.

V Conclusions

This research work concludes that the highest accuracy value is 88.02% of accuracy level which is acquired by n-neighbors=5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The highest positive predictive value value is 0.87 which is owned by n-neighbors=5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The maximum as well same Sensitivity value is 0.88 which yielded by n-neighbors =3 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The highest F-Measure value is 0.86 is produced n-neighbors =3 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model, n-neighbors =7 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The supreme value of Mean Square Contingency Coefficient shows that 0.45 which is given by n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The maximum amount of kappa value is 0.42 which is picked by n-neighbors =3 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and

Manhattan distance function model. The highest ROC value is 0.80 which is given by n-neighbors =9 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. Highest PRC value is 0.87 which is given by there are two models. They are n-neighbors =7 and n-neighbors =9 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function models. The Least Mean absolute deviation is 0.16 which is given by is shown by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The least root mean squared deviation is 0.31 which are demonstrated by n-neighbors =5 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The smallest relative absolute error performance is 61.66 %which is hold by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. The largest root relative squared error performance is 110.98 %which is hold by n-neighbors =1 with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model. This research work recommended that the n-neighbors =5 by applying various n-neighbors with 1.0 of default radius,30 of leaf size, minkowski of distance metric, Ball Tree of Nearest Neighbor Searching algorithm, without parallel job, and Manhattan distance function model.

VI. Conflicts of Interest

The authors declare no conflict of interest.

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