Predicting Pavement Condition Index Using an ML Approach for a Municipal Street Network

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Abstract: Machine learning (ML) models are increasingly getting attention in predicting pavement maintenance methods to improve decision-making. This study investigates the use of ML at the municipal level to predict the street pavement condition index (PCI) rating over a 4-year span. Several supervised learning models, namely linear regression (LR), random forest (RF), and neural network (NN), were applied to the visually assessed pavement condition data of Skellefteå municipality, Sweden. Pavement distress, pavement age, and traffic data were used in several combinations to evaluate and compare the performance of the models. The RF model was based on paired variables of pavement age and pavement distress data. The results were comparatively accurate with $R^2 = 0.59$ and Spearman's coefficient $= 0.74$ for residential streets in the model testing stage. Similarly, for main, collector, and industrial (MCI) streets, the RF model, based on pavement age and traffic variables, performed best with $R^2 = 0.79$ and Spearman's coefficient $= 0.88$ during the model testing stage. The importance of input variables varies with the level of the model's sophistication and pavement performance goal; however, pavement age is the dominant variable. The prediction models can be useful in effectively managing street networks among municipalities, even those with scarce resources.
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Introduction

Pavement infrastructure plays an important role in the socioeconomic development of any municipality. Deterioration of street pavement is a complex phenomenon due to highly variable traffic volume and axle loads, environmental conditions, and maintenance approaches throughout the service life of the pavement (Mallick and El-Korchi 2013; Sun 2016). Maintaining the road network in a desired condition is a challenge due to insufficient maintenance budgets across the vast majority of pavement management administrations, particularly at the municipality level. Thus, a cost-effective and sustainable pavement maintenance approach is required, which can be achieved through objective decision-making.

Pavement management systems (PMS) has been recognized as a useful tool to maintain street networks at the required service level with the help of current and historical pavement data and the future predicted condition of streets (El-Diraby et al. 2017; Gao et al. 2021). PMS generally include pavement data, pavement condition indices, pavement deterioration/prediction models, and digital interactive maps (Haas et al. 2015).

Pavement condition data (surface distress, roughness, structural capacity) can be collected both at the network level and project level in the PMS. Such data can be collected manually (visual survey/windshield) or automated (Coenen and Golroo 2017), depending on the pavement performance goals and maintenance budget of the municipalities. In this regard, monitoring the performance trends of the pavement network over time is dependent on the quality and availability of the data (Cesme et al. 2017). Due to the significance of quality pavement condition data in the effectiveness of PMS, a data quality management system should be in place to oversee the collected data quality (Flintsch and McGhee 2009).

Pavement performance indices have been widely used as part of PMS, e.g., pavement condition index (PCI), present serviceability index (PSI), international roughness index (IRI), and present serviceability rating (PSR) (Nabipour et al. 2019). PCI is one of the most common performance indices (Hu et al. 2022; Piryonesi 2019). Several studies have been conducted to use simplified PCI with a reduced number of distresses in order to reduce the PMS cost (Kheirati and Golroo 2022).

Pavement performance models play a vital role in pavement management, since these models predict pavement deterioration/future conditions based on influencing factors like traffic, climate, pavement condition, and historical data (Marcelino et al. 2021). Pavement condition prediction models require regular pavement inventory as well as a well-maintained database for registering the assessment and storing the maintenance history of the pavement network (Gao et al. 2022). Similarly, the accuracy of the prediction model needs to be reasonably good since it is strongly correlated to the cost of maintenance and rehabilitation activities (Hosseini and Smadi 2021). Earlier studies have highlighted the importance of

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both deterministic and stochastic pavement performance prediction models in the PMS (Amin 2015; Robinson et al. 1998; Sadeghi et al. 2017). Deterministic models predict the specific value of a dependent variable, e.g., pavement condition based on the independent variables (Martin and Sen 2023; Wolters and Zimmerman 2010). On the other hand, probabilistic models predict a range of values of the dependent variable (Robinson et al. 1998; Wolters and Zimmerman 2010). Machine learning (ML) models for assessing and predicting the pavement performance, either deterministic or probabilistic (Haddad et al. 2022), have also been extensively utilized in PMS (Kargah-Ostadi and Stoffels 2015).

ML algorithms have been used both in the pre-and postpavement condition data analysis as part of PMS. In predata analysis, ML algorithms have been applied in the automated collection of surface distress on the pavements, such as cracks and potholes (Cui et al. 2015; Majidifard et al. 2020), while visually collected input distress variables have been used to determine PCI in postdata analysis (Issa et al. 2022; Sharma and Kumar 2022).

One widely applied ML technique is the artificial neural network (ANN), which has been a useful regression model for predicting the condition of pavement segments (Abambres and Ferreira 2017; Issa et al. 2022; Kaya et al. 2020). For instance, Sirhan et al. (2022) conducted a study to predict the PCI and the relative importance of input variables (11 distresses) using a deep neural network (DNN) model. Their finding strongly suggests the incorporation of DNN in the PMS due to its accurate performance. Furthermore, the ANN model was applied to predict the quality of rides, cracks, and ruts (Alharbi 2018). The finding reflects better performance through ANN models compared to multiple linear regression (MLR) models. Another comparative study of several deterioration models revealed that ANN models were more accurate than the traditional regression models in predicting the overall condition of the pavement (Yang et al. 2003). Similarly, Suman and Sinha (2012) concluded that the observed PCI rating and pavement age as input variables in ANN models are effective in forecasting the pavement condition and improving maintenance approaches in the long run. Moreover, ANN models performed comparatively better in forecasting the PCI through manually/visually collected pavement data.

Similar to the ANN model, the random forest (RF) model has also been utilized to predict pavement performance. In one study, the RF model showed better results ($R = 0.84$) compared to Gaussian process regression (GPR) and M5P model trees for predicting the pavement capacity (Karballaeezadeh et al. 2020). A study conducted by Olowosulu et al. (2022) revealed that RF and decision tree (DT) algorithms were better data-mining techniques compared to the naïve Bayes (NB) algorithm for predicting the pavement status classifications. In another study, ANN and support vector machine (SVM) models showed better accuracy, based on 14 distresses, in predicting the PCI relative to RF (Kumar et al. 2021). Another comparative study of ANN, SVM, and RF models recommended the RF approach in predicting the IRI, even with fewer data sets (Aranha et al. 2023).

Partly missing pavement data is a common issue in most PMS or research studies (Al-Zou'bi et al. 2015; Marcelino et al. 2021) for predicting the future condition of the pavements. Historically, this issue has been addressed through two approaches, i.e., either ignoring the pavement segments with lack of data or imputing (predicting) the missing data (Al-Zou'bi et al. 2015; Gao et al. 2022; Marcelino et al. 2021). In this regard, pavement condition data variables and nonpavement auxiliary variables—equivalent single-axle loads (ESAL) and falling weight deflectometer (FWD) data—were used by Farhan and Fwa (2015) to impute the missing data. Furthermore, Zhao et al. (2018) used a spatial dependency model to predict the pavement deterioration rate through both its degradation history and the history of the neighboring pavement.

A recent survey revealed that the use of PMS among Swedish municipalities is limited, while the sophistication of PMS is low due to the lack of pavement prediction models and maintenance history (Afridi et al. 2023). The study revealed further that the implementation of PMS is highly dependent on the availability of budget and resources, along with the size of the street network. Small municipalities with small network sizes and scarce resources prefer to use an in-house traditional pavement management approach instead of PMS. In general, municipalities lack written guidelines for selecting the maintenance treatment and instead rely on experience-based decision-making. Furthermore, the majority of municipalities use the windshield/visual assessment method to evaluate the pavement condition while the use of a sensor-based approach is rare (Afridi et al. 2023).

The objective of this study is to develop a simple rational method to contribute to pavement maintenance decision-making and optimal utilization of the maintenance budget at the municipal level in Sweden while simultaneously providing an acceptable level of service for road users. This study is based on a case study conducted in Skellefteå municipality to apply a smart maintenance approach in maintaining the municipality's street network. Comparative supervised ML models (NN, RF) and linear regression (LR) models were used to forecast the pavement conditions at the network level of residential, main, collector, and industrial (MCI) streets, based on the visually assessed pavement data. Further analysis was carried out to investigate the importance of input variables and the usefulness of subjective data in predicting pavement status.

Data Descriptions

Database for the ML Model

The study was carried out on the pavement network of Skellefteå municipality, which is in the northern part of Sweden with a population of 72,000 inhabitants. Skellefteå municipality is situated in climate zone 5, the coldest among Sweden's five climate zones, characterized by its typically cold and prolonged winters and short summers (Trafikverket 2011). Furthermore, in this climate zone, the frost depth in the pavement normally exceeds 2 m, while the air freezing index ranges from approximately 550 to 2,200 degree days per year (Erlingsson and Saliko 2020). The municipality has a winter maintenance strategy where ploughing and sanding are the main maintenance activities/operations to enhance safety and adequate friction on the pavement surface, while salting is limited and is only applied to prevent ice formation on street pavement surfaces during transition periods in autumn and spring.

Pavement data used in the study (Fig. 1) were retrieved from Skellefteå municipality, which has a street pavement network of about 410 km in length. However, the retrieved data are limited since the pavement data are stored in different databases. Pavement surface condition assessments were conducted by the municipality in 2014 and 2018, using the windshield surveys approach at the network level. Pavement assessments were outsourced to the same contractor, and experts rated the distresses during postprocessing, using global positioning system (GPS)-coordinated images taken during the windshield survey. In essence, the assessment of pavement condition was entirely subjective, relying on the experiences of experts. The pavement network is divided into four street classes based on their functionality: main streets, collector streets, local/residential streets, and industrial streets. Similarly, the pavement

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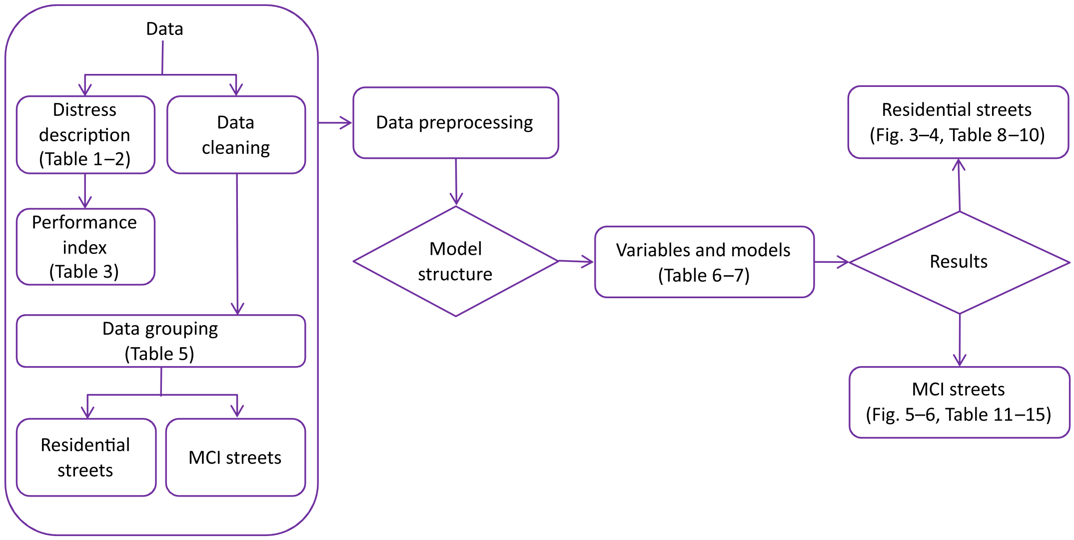

Fig. 1. Flow chart of data and models.

network is divided into about 3,950 segments based on their condition, which means that the length of the segments is not constant (most segments are around 100 m in length). In the survey, the severity and density of six pavement surface distresses were collected to assess the pavement performance, which included surface unevenness *SU* (longitudinal and transversal directions, excluding rutting); alligator cracking *ACR*; cracks *CR* (longitudinal, transversal, frost, edge, joint reflection, etc.); rutting *RUT*; raveling *LAR* (loss of coarse aggregates), including asphalt hardening; and miscellaneous surface defects *SD*, e.g., patching, potholes, edge deformation.

The Skellefteå municipality utilizes the PCI as the performance index, which ranges from 0 to 100. A PCI rating of 100 indicates excellent condition, whereas a rating of 0 reflects the worst surface condition of the pavement segments. In this context, experts utilize Table 1 to assess pavement condition, incorporating severity and density levels of various pavement distress types based on their experiences. This table was developed locally using guidelines from the pavement condition assessment handbook (Wågberg 2003). Similar handbooks have been developed both in the United States and in other European countries (Miller and Bellinger 2014; Ragnoli et al. 2018). According to Table 1, the severity levels indicate the degree of the distress type, while density levels indicate the extent of pavement surface affected, aligning with the corresponding difficulty levels, which serve as indicators of the level of complexity in addressing the distress type. In simpler terms, as the difficulty levels increase, addressing pavement distress becomes challenging, indicating a higher level of pavement deterioration. This is reflected through deducted points in the PCI rating computation of a pavement segment.

Table 1. Guidelines for assessment of pavement conditions

		Density levels			
Distress type	Severity level	Affected pavement	Difficulty Level I (deduct points)	Difficulty Level II (deduct points)	Difficulty Level III (deduct points)
Surface unevenness	Low	≤20%	20	35	50
	Moderate	20%–50%	35	50	65
	High	≥50%	50	65	70
Alligator cracking	Low	≤20%	30	45	60
	Moderate	20%–50%	45	60	75
	High	≥50%	60	75	85
Longitudinal/transverse cracking	Low	≤20%	5	15	30
	Moderate	20%–50%	15	30	50
	High	≥50%	30	50	75
Rutting	Low	≤20%	15	40	70
	Moderate	20%–50%	15	40	70
	High	≥50%	15	40	70
Raveling, including asphalt hardening	Low	≤20%	5	15	30
	Moderate	20%–50%	15	30	50
	High	≥50%	30	50	75
Miscellaneous surface defects	Low	≤20%	5	10	20
	Moderate	20%–50%	10	20	40
	High	≥50%	20	40	60

Table 2. Pavement segment status classification and their descriptions

Pavement condition category	PCI rating	Approximate remaining service life	Condition description
Green	81–100	More than 10 years	Good, no need for maintenance
Yellow	61–80	6–10 years	Fair, needs maintenance
Red	41–60	3–6 years	Poor, needs immediate maintenance
Black	0–40	0–3 years	Very poor, needs reconstruction

The pavement conditions are classified into four categories—green, yellow, red, and black—based on the PCI ratings, as described in Table 2. These categories also serve as indicators for the timing of maintenance activities. A similar approach has been adopted in the United States (CMAP 2024; Laton 2020; ODOT 2006). The municipality uses the following equations (Estholm 2019; Shahin 2005) to calculate the PCI rating or pavement condition of street segments:

Fig. 2. Residential street in need of reconstruction (black category segment), located in Skellefteå municipality. (Image courtesy of Skellefteå Municipality.)

$$\text{PCI rating} = 100 - WDV \quad (1)$$

where WDV is the weighted deduct value, $0.63636 \times (x - 10) - 0.001715 \times (x - 10) \times (x - 120)$, where x is the total deduct value, which is the sum of all deduct values of distresses on the pavement section.

An example of pavement condition assessment for a street (Fig. 2) is presented in Fig. 3. The pavement data in Fig. 3 highlights the geometry, distress types, severity, and density of distress for this particular street segment, categorized under the black category, indicating the need for reconstruction.

Pavement Data for the Model

The selection of pavement segments in the model data was based purely on the availability of maintenance history for the pavement segments in the municipality's PMS database. Pavement maintenance activity data have been stored in the maintenance database since 2002. The maintenance history for most of the network includes the name of the street and functional class; the type and layer thickness of material used; the length and width of the pavement; traffic data; and the cost of maintenance measures. The quality of information stored in the database has been improved over the years.

In the data preprocessing, maintenance data held in the municipality's PMS database for street pavements between 2002 and 2018 were retrieved. During the process, it became apparent that some street segments were inadequately documented, with issues such as inconsistent PCI ratings and missing traffic data.

Chart evaluation of street				
Street class	3			
Street name	Norra Strandgatan			
Street segment	897			
Length (m)	170.12			
Width (m)	6			
Area (m^2)	1020.72			
	Severity of Distress			**Deduct value**
Distress type	**Low ≤20%**	**Medium 20% – 50%**	**High ≥50%**	**(Points)**
SU	-	-	Yes	70
ACR	-	-	-	-
CR	-	-	Yes	50
RUT	-	-	-	-
LAR	-	-	Yes	50
SD	-	-	-	-
Total Deduct Value (*x*)				170
WDV = 0.63636*(*x*-10)-0.001715*(*x*-10)*(x-120)				88.10
PCI rating = 100 - *WDV*				11.90
Remarks: The condition of the pavement segment is "black" as per Table 2				

Fig. 3. Street pavement condition assessment form within PMS.

Table 3. Street segments that are used in the models

Street groups	Class	Street classification	Length (km)	Number of street segments
MCI streets (nonresidential streets)	1	Main streets	50 out of 60	431
	2	Collector streets	5 out of 19	51
	4	Industrial streets	3 out of 11	12
Residential streets	3	Residential streets	262 out of 322	2,530
Total			320 out of 429	3,024

Consequently, nearly 22% of the street network was excluded from the study. The maintenance history of pavement segments includes maintenance year, maintenance treatment, and maintenance material. The maintenance data are further categorized concerning the cost of treatment. The PMS databases include pavement thickness data on most of the reconstructed pavements since 2010. Consequently, the majority of streets with a well-documented pavement history are nonresidential streets and are in the green category. The pavement age of residential streets that lack maintenance history was estimated based on the maintenance/rehabilitation history and PCI rating of the neighboring streets or neighborhoods, and the approximate year of construction of streets in the municipality. In this regard, the black category streets with no information about maintenance history were considered about 35–40 years old, the red category 25–30 years old, and the yellow category 15–20 years old.

The frequently applied maintenance treatments in the municipality are thin overlay (1–2.5 cm) of asphalt concrete and milling followed by overlaying with 2–3 cm of asphalt concrete (Anderson-Skold et al. 2022). Other maintenance treatments include crack sealing, patching, and reconstruction of streets.

The traffic database includes traffic volume, heavy traffic, and the speed limit on street segments. However, the municipality does not collect traffic data for all streets; as a result, some of the street segments were missing traffic data.

Climate data have not been included in the analysis since they does not vary significantly in the municipality, i.e., from one neighborhood to another as per the recent climate data.

After examining the pavement data, it was decided to use traffic data, surface distress data, and PCI rating for pavement assessment in 2014 in the models, together with the maintenance history up to 2018. In other words, the pavement condition observed in 2014 was used as a baseline to predict the PCI rating in 2018. The number of street segments is 3,024 with a total length of 320 km, as shown in Table 3. Moreover, it can be seen that street classes 1, 2, and 4 were included in one group (MCI streets or nonresidential streets) and class 3 in another group (residential streets). A comparative analysis of each model's performance was carried out for both groups of streets. Table 3 shows that the street pavement data used in the models represent 75% of the total street network in length.

Methodology

Model Structure

As described in Table 4, several variables have been utilized in the study. Age refers to the time since the last period of maintenance or rehabilitation that a street section has received, i.e., the age of the wearing surface (asphalt concrete). The criteria for assigning the deduct values for pavement distress during the pavement condition assessment are provided in Table 1. Moreover, traffic volume on MCI streets is separated into the variables light traffic and heavy traffic. All the variables are combined in several ways to analyze the performance of models for both groups of streets, as presented in Table 5.

In data preprocessing, the scaling of the original data was carried out before running the models. For the training RF model, two tuning parameters were specified: ntree and mtry. ntree represents a number of variables, which are randomly collected and sampled at each split time, whereas mtry is the number of branches that will grow after each time split. More specifically, different values were tested for both ntree and mtry, ranging from 250–1,000 for ntree, and 2–10 for mtry. For training neural networks, two hyperparameters were specified: size and decay. Size is the number of units in the hidden layer, while decay is the regularization parameter to avoid overfitting. More specifically, different sizes were tested, ranging from 1 to half the number of inputs, and decay from 0.1–0.5.

Table 4. Description of variables used in the study

Variables	Acronym	Description
Age	A	Time since last maintenance treatment up to 2018.
Deduct values of distresses	D	Deduct value assessment of different distresses (SU, ACR, CR, RUT, LAR, SD), based on Table 1. Pavement condition D as per the 2014 assessment.
Traffic	$T = LT + HT$	Average weekday traffic includes both light traffic (LT) and heavy traffic (HT).

Table 5. Description of variables and models used in the study (for both residential and nonresidential streets)

Variables	Models and acronym	Description
A	Simple linear regression (LR simple)	Model is based on a single variable, age.
A and D	Linear regression (LR), random forest (RF), neural network (NN)	Linear regression and well-known supervised machine learning approaches.
A and T	Linear regression (LR), random forest (RF), neural network (NN)	
A, D, and T	Linear regression (LR), random forest (RF), neural network (NN)	

Note that for residential streets, traffic data were excluded from the models since traffic volumes are quite low. In contrast, models for MCI streets include a variable related to the amount of traffic data. Unfortunately, approximately 5% of the MCI streets are missing traffic data values. The missing traffic data were imputed by using the k-nearest neighbor (KNN) algorithm, a common method for addressing missing data issues (Murti et al. 2019; Sallaby and Azlan 2021). In this regard, the number of neighbors used in the imputation, k, was set as the closest integer to the square root of the number of observations (i.e., street segments).

Performance Evaluation of Models

Performance metrics are essential for evaluating the quality and effectiveness of predictive models. The models' goodness of fit and predictive power were evaluated (Ali et al. 2023; Karballaeezadeh et al. 2020) using the following performance measures.

Mean absolute error (MAE) measures the average of the residuals:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}| \tag{2}$$

Root-mean-square error (RMSE) measures the standard deviation of residuals:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2} \tag{3}$$

The coefficient of determination (R^2) represents the proportion of the variance in the dependent variable, which is explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{4}$$

where N is the number of street segments, y is the street segment, $\hat{y}$ is predicted value of y, and $\bar{y}$ is a mean value of y.

Note that low values for MAE and RMSE are good and imply higher accuracy of a model. However, high values close to 1 or negative 1 are good for R^2. RMSE gives larger penalization to high prediction errors, while MAE treats all errors the same.

All algorithms and comparisons were conducted using the R programming language. The *caret2* (classification and regression training) package was utilized for algorithms, while the *VIM3* (visualization and imputation of missing values) package was employed for the imputation of missing values. The seed for a random number generator was set to make the results reproducible by other researchers; specifically, the list of random numbers was started at position 123.

The effectiveness of the models was evaluated using a cross-validation technique. Therefore, the data were split into training and testing to avoid testing data that had already been used for training the models. Data were split into 10 folds and the process was repeated 10 times. In each cross-validation iteration, the data were randomly divided into 10 subsamples of approximately equal size whereby each subsample was used once as testing data and the remaining data were used for training. By repeating the process 10 times, 100 values of MAE, RMSE, and R^2 were obtained. Furthermore, during the model testing phase, the predicted and observed PCI were plotted and determined R^2 and Spearman's rank correlation coefficients.

Finally, to explain the prediction of models, the importance (weighting) of variables was calculated by using different explainable ML techniques. In this regard, the absolute value of the t-statistic was used for each model parameter for LR models, Shapley additive explanations (SHAP) values for RF, and combinations of the absolute values of the weights for NN.

Results

The average performance of the models constructed for residential and MCI streets was studied. Additionally, box plots, depicting the 25th percentile, median, and 75th percentile values of the distributions of MAE, RMSE, and R^2, were included to visualize the performance of different models across various folds. The results are based on the observed pavement condition in 2014, which included nine input variables in several combinations to predict the PCI rating of the pavement segment for the year 2018. The predicted PCI rating was plotted against the observed PCI rating for 2018 to measure the correlation coefficients. Finally, the importance of variables in predicting the PCI rating was analyzed for each group of models.

Residential Streets

It can be seen in Table 6 that the RF model built on variables A and D performs better in the prediction of the status of street segments, followed by the NN, LR, and LR simple models. This order of performance is the same in MAE, RMSE, and R^2 evaluation matrices in the 10-fold cross-validation phase. By comparing the percentage difference of MAE values, the RF model is 6%–24% better, while in the case of RMSE values, the RF model is 6%–21% better than the NN, LR and LR simple models. Similarly, by comparing R^2 values, one can see that the RF model performance is roughly improved by 13%–43% compared to the rest of the models.

It can be observed in Fig. 4 that the order of the models according to their performance is the same in terms of MAE, RMSE, and R^2, and that the difference in performance is significant. In Fig. 5, predicted versus observed ratings of PCI were plotted to assess the correlation between the two variables. The correlation seems to be linearly positive in all models, which produced a range for R^2 from 0.30 to 0.59 in the model testing stage. Moreover, it is observed that predictions from the RF model are closer to a regressed diagonal line compared to those from the NN, LR, and LR simple models.

However, it is observed that predictions are close but do not necessarily follow a straight line; therefore, the relationship may be described by some monotonic function. To study this further, Spearman's correlation was calculated to assess the pairwise degree of association between predicted and observed values. In Table 7, it can be seen that the Spearman's correlation between predicted and observed values from RF is stronger than for the other models.

Furthermore, the influence of each input variable was calculated to determine the importance of variables in the output of the model. In this context, Table 8 highlights that variable A holds the highest importance across all models, while the ranking order of the other variables varies between models. Notably, variable SD has the

Table 6. Median values of the performance measures for residential streets, assessed using 10-fold cross-validation

Model name	Variables	MAE	RMSE	R^2
LR simple	A	13.8	17.54	0.30
LR	$A + D$	12.77	16.43	0.38
RF	$A + D$	11.17	14.55	0.53
NN	$A + D$	11.88	15.4	0.46

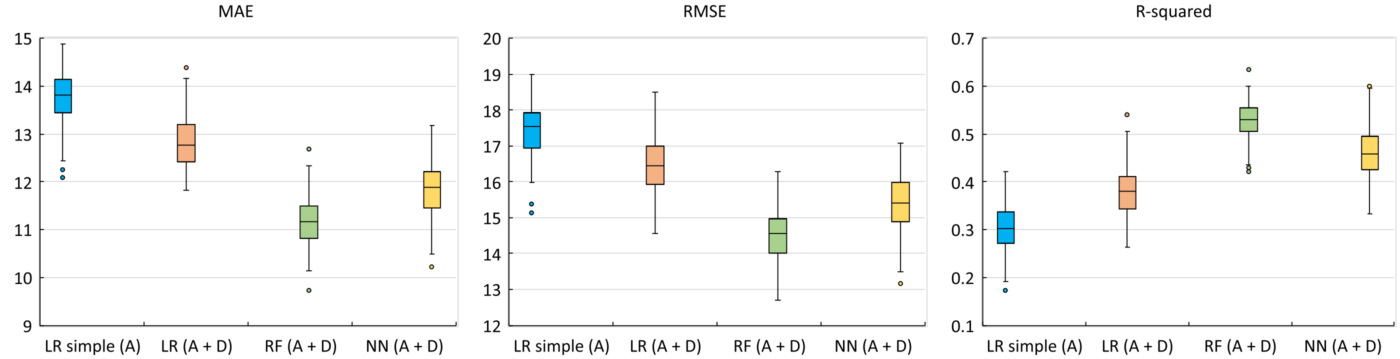

Fig. 4. Comparison of model performance for residential streets, assessed using 10-fold cross-validation.

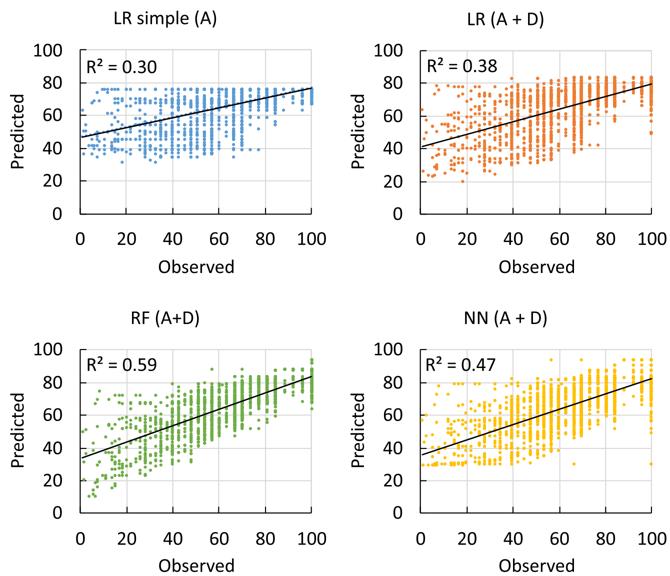

Fig. 5. Accuracy of the LR simple and state-of-the-art supervised models for residential streets in the model testing stage.

Table 7. Spearman's rank correlation coefficient for residential streets

Model name	Variables	Spearman's rank correlation
LR simple	A	0.52
LR	$A+D$	0.61
RF	$A+D$	0.74
NN	$A+D$	0.66

lowest contribution for LR and RF, while it is ranked as the second-least important for NN.

MCI Streets—Nonresidential Streets

From Table 9, it is evident that the RF model outperformed the NN, LR, and LR simple models in the 10-fold cross-validation phase. Moreover, it can be seen that the RF model built on $A+T$ variables performed best, with MAE $= 7.45$, RMSE $= 11.3$, and $R^2 = 0.50$. Subsequently, the RF model constructed with $A+D+T$ variables and $A+D$ variables followed in performance. The RF $(A+T)$ model performed better with a range of 10%–55% and 1%–30% in the case of MAE and RMSE evaluations, respectively. Similarly, by comparing the R^2 evaluation values, it can be seen that the performance of the models decreases from 2% to 74% with respect to the RF $(A+T)$ model.

Table 8. Variables ordered by their importance for residential streets

Variable importance order	LR	RF	NN
1	*A*	*A*	*A*
2	*CR*	*SU*	*SU*
3	*SU*	*LAR*	*ACR*
4	*LAR*	*CR*	*LAR*
5	*ACR*	*ACR*	*SD*
6	*SD*	*SD*	*CR*

Table 9. Median values of the performance measures for MCI streets, assessed using 10-fold cross-validation

Model name	Variables	MAE	RMSE	R^2
LR simple	A	11.55	14.68	0.13
LR	$A+D$	10.91	13.90	0.18
	$A+T$	11.48	14.51	0.15
	$A+D+T$	10.98	14.35	0.19
RF	$A+D$	9.81	13.20	0.31
	$A+T$	7.45	11.30	0.50
	$A+D+T$	8.17	11.42	0.49
NN	$A+D$	10.01	13.38	0.26
	$A+T$	11.04	14.11	0.18
	$A+D+T$	10.08	13.66	0.23

Fig. 6 shows that the difference in performance is significant in terms of MAE, RMSE, and R^2 between those that perform well and those that perform badly, but the difference is not significant for those in the middle. Furthermore, it can also be seen that the order of the models by their performance is similar in terms of MAE and RMSE but is slightly different in terms of R^2.

To assess the model's accuracy, predicted versus observed values were plotted during the model testing stage. From Fig. 7, it can be seen that different combinations of variables produced a wide range for R^2 from 0.14 to 0.79. Furthermore, it can be observed that predictions from RF built on $A+T$ variables and on $A+D+T$ variables are closer than for other models to a regressed diagonal line. However, it was noted that the predictions might be close but do not follow a straight line; the relationship, therefore, might be described by some monotonic function. The Spearman's correlation coefficient was also calculated for this group of streets. Table 10 shows that the RF model predictions based on $A+T$ and $A+D+T$ variables have a stronger relationship with observed

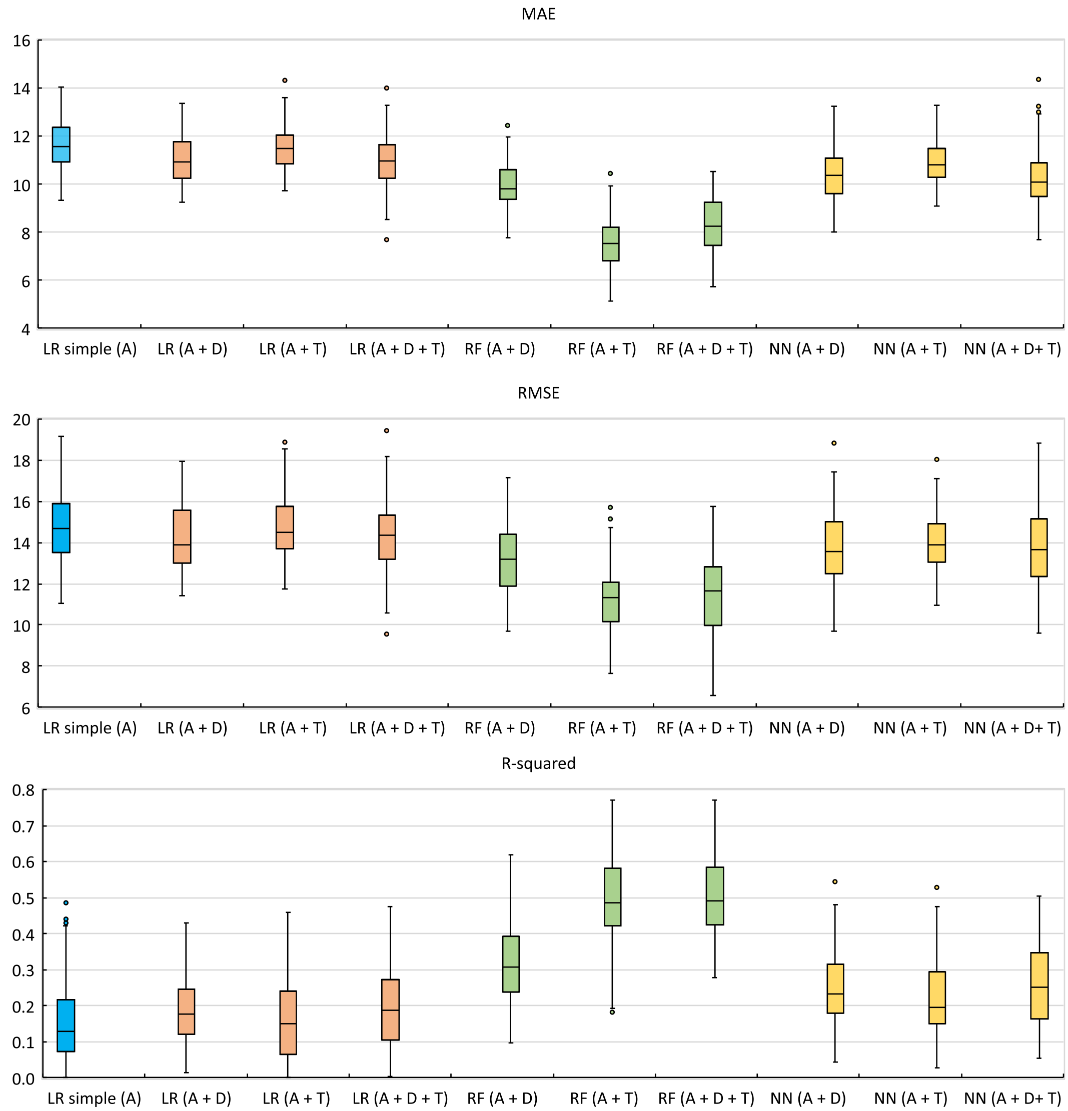

Fig. 6. Performance comparison for MCI streets. The middle line in the box represents the median, assessed using 10-fold cross-validation.

values compared to the other models. It can be seen that the values of Spearman's coefficient indicate a monotonic relationship between predicted and observed PCI ratings across all models.

For each model, the influence of each input variable was calculated to determine the importance of each variable. Table 11 shows that A is the most important variable for all the models built on $A + D$; however, the order of the other variables differs between the models. For example, ACR is less important for both NN and RF but is quite important for LR.

However, Table 12 shows that for the RF built on the $A + T$, the LT variable is more important than A. Furthermore, Table 13 highlights that the A variable is again the most important one and ACR is a less important variable for both NN and RF but not for LR. Variables LT and HT are quite important for RF but are less important for both LR and NN; the order of importance also changes.

Discussion

Residential Streets

The performance of models for residential streets varies when analyzing the model evaluation matrices using 10-fold cross-validation (Table 6), and R^2 (Fig. 5), Spearman's coefficient value (Table 7), and the order of variable importance (Table 8) during the testing stage. RF models performed best throughout the aforementioned evaluations. RF models explain the data better, with an R^2 value of 0.5 using the 10-fold cross-validation. In other words, the RF model accounts for half the variance in the data, reflecting the complexity of the problem to the model's ability to learn. Similarly, the best RMSE value is about 14 for RF, which is better compared to the other models. During the model testing stage, the highest R^2 value between the predicted and observed PCI ratings is 0.59, while the highest monotonic relationship, as indicated by Spearman's coefficient, is 0.74.

High Spearman's coefficient values indicate a strong positive monotonic relationship between the variables. The improvement in the Spearman's coefficient increases with decreasing R^2 values, from LR simple to the RF model. This could be due to the lower sensitivity of Spearman's coefficient to outliers. It could be argued that either the RF model might be useful in managing the outliers or it is less sensitive to outliers in predicting the future status.

In the case of residential streets, pavement age and pavement distress were utilized as input variables, while pavement age and maintenance history are highly important variables for predicting the PCI rating of streets. Similarly, pavement distress data are

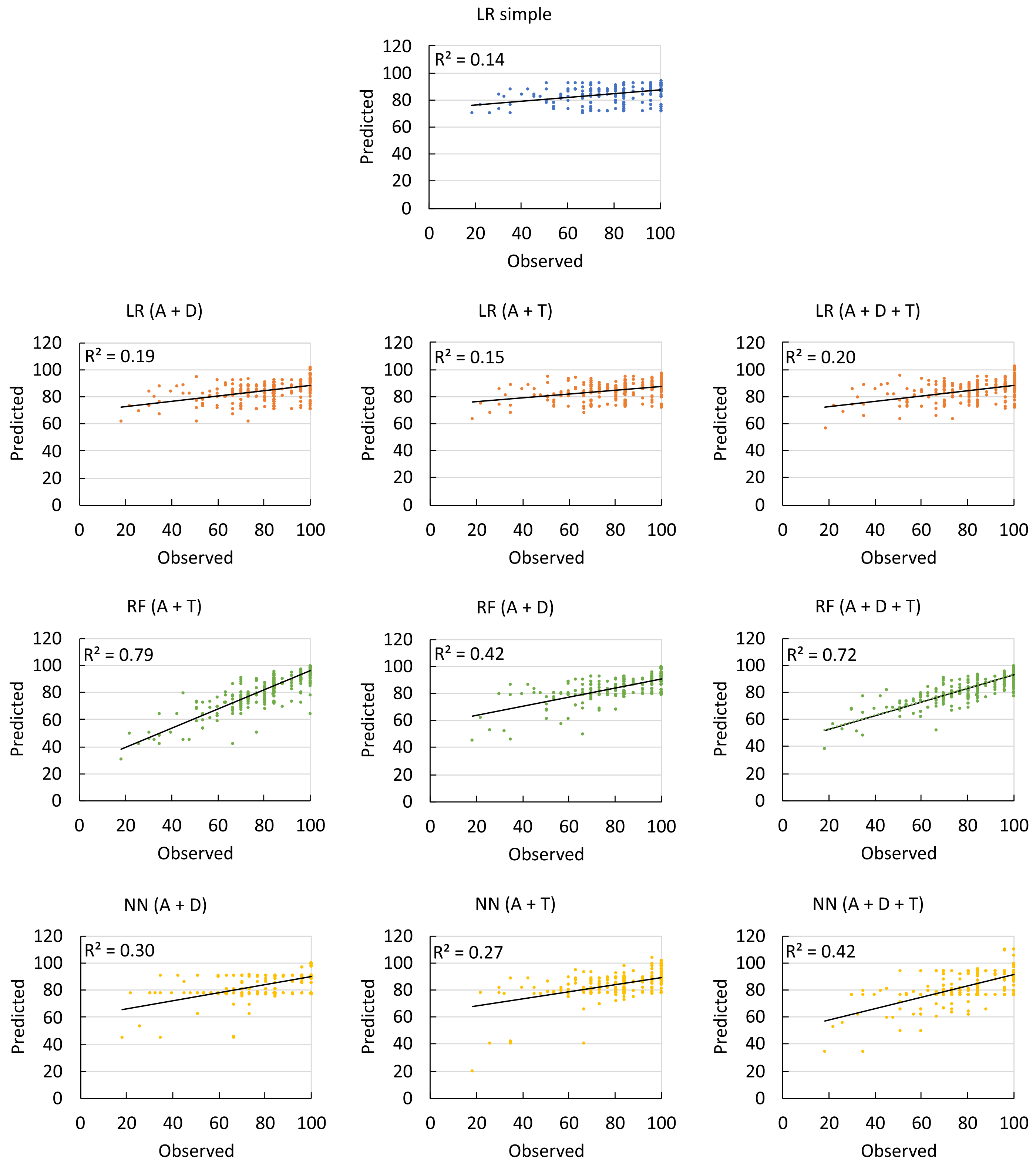

Fig. 7. Accuracy of models for MCI streets with respect to the 2018 assessment during the model testing stage.

important in the timely maintenance of pavement. However, *SU*, *LAR*, and *CR* are the most important variables followed by pavement age for residential streets in predicting the PCI rating. *SU*, *LAR*, and *CR* are equally related to pavement age and cold climate. Climate is not one of the variables, but it has a great influence on the deterioration of pavements in the region. Regular collection of pavement distresses would help in improving the performance of the models. It may be interesting to use this model in densely populated municipalities by adding traffic information.

MCI Streets—Nonresidential Streets

The performance of models for MCI streets, like for residential streets, varies in the model evaluation matrices using 10-fold

Table 10. Spearman's rank correlation coefficient for MCI streets

Model name	Variables	Spearman's correlation
LR simple	A	0.40
LR	$A+D$	0.45
	$A+T$	0.39
	$A+D+T$	0.45
RF	$A+D$	0.66
	$A+T$	0.88
	$A+D+T$	0.85
NN	$A+D$	0.57
	$A+T$	0.49
	$A+D+T$	0.62

Table 11. Variables ordered by their importance for models built on $A+D$ for MCI streets

Variable importance order	LR	RF	NN
1	*A*	*A*	*A*
2	*CR*	*CR*	*RUT*
3	*SD*	*LAR*	*CR*
4	*ACR*	*RUT*	*LAR*
5	*RUT*	*SD*	*SU*
6	*LAR*	*SU*	*SD*
7	*SU*	*ACR*	*ACR*

Table 12. Variables ordered by their importance for models built on $A+T$ for MCI streets

Variable importance order	LR	RF	NN
1	*A*	*LT*	*A*
2	*HT*	*A*	*HT*
3	*LT*	*HT*	*LT*

Table 13. Variables ordered by their importance for models built on $A+D+T$ for MCI streets

Variable importance order	LR	RF	NN
1	*A*	*A*	*A*
2	*CR*	*LT*	*SU*
3	*ACR*	*HT*	*CR*
4	*HT*	*LAR*	*HT*
5	*SD*	*CR*	*RUT*
6	*RUT*	*RUT*	*LAR*
7	*LT*	*SD*	*SD*
8	*SU*	*SU*	*LT*
9	*LAR*	*ACR*	*ACR*

cross-validation (Table 9 and Fig. 6), and R^2 (Fig. 7), Spearman's coefficient value (Table 10), and the order of variable importance (Tables 11–13) in the testing stage. Thus, variables are utilized in 10 different ways to determine the aforementioned evaluation. The results show that the performance of models varies with the combination of input variables.

The pavement age and traffic ($A+T$) pair of variables performed well on MCI streets to forecast the pavement condition in the RF algorithm (Fig. 7). The difference in the performance of $A+T$ and $A+D+T$ is small, but it is interesting that by adding distresses as a third variable, the RF model accuracy decreases slightly. Conversely, the performance of the LR simple, LR, and NN models improves, though the RF model performs even better. Nevertheless, pavement age and traffic information are sufficient for predicting the PCI rating of MCI streets in the current study without nullifying the importance of regular assessment of pavement networks. Regular assessment of the street network would improve optimization of the models. RF models explain the variation in data better, with an R^2 value of 0.5 in the 10-fold cross validation. The best RMSE value is about 11, while the best correlation between the predicted and observed values is 0.79 for RF models with pavement age and traffic as input variables.

During the model testing stage, a high Spearman's correlation was observed between the predicted and observed PCI ratings in all the models. The correlation between the predicted and observed values is strongly positive monotonic, particularly in the case of RF with $A+T$ and $A+D+T$, respectively. The improvement in the Spearman's coefficient is similar to residential models, i.e., increasing with decreasing R^2 values. Similarly, the result of the RF model suggests that RF is better at managing the outliers due to splitting the data into several decision trees.

The order of importance of input variables varies among models (Tables 11–13). Pavement age is highly important in all the models, followed by *CR* and traffic. Understandably, the more aged the pavement is, the higher the risk of *CR* distress appearing on MCI streets due to climate and traffic. Interestingly, traffic is more significant than distress in RF models in predicting the PCI rating. This significance is in contrast to the rest of the MCI models.

Significance of Models

The Skellefteå municipality employs the pavement condition category as a framework for organizing their annual maintenance activities. Tables 14 and 15 provide a comparative summary of model prediction accuracy across various street condition categories and overall accuracy for residential and nonresidential streets, respectively.

Notably, the residential RF model appears to be the most effective overall (54% accuracy), followed closely by the NN model (48%). Each model demonstrates varying strengths across different pavement condition categories. For instance, NN performs best in predicting the green category streets, LR simple has a notably high accuracy in the yellow category, and RF achieves the highest accuracy in predicting both the red and black categories. The choice of model for residential streets may depend on specific priorities, such as accurately predicting different pavement condition categories or achieving a high overall accuracy.

In the case of nonresidential streets, the RF ($A+T$) model achieves the highest overall accuracy at 84%, followed closely by RF ($A+D+T$). However, the accuracy diminishes with lower pavement condition categories, potentially tied to data imbalance and subjective pavement condition assessments. NN models show varying overall performance across variable combinations, suggesting sensitivity to the input variables. The choice of the best-performing model depends on the specific street condition category and the combination of input variables considered. RF, especially with *A* and *T* variables, tends to perform well across categories and is particularly strong in the green and yellow categories.

The variance in overall prediction accuracy between residential and nonresidential models is marginal, not exceeding 16% between the most and least accurate models. While the models do not achieve high accuracy in predicting PCI ratings, they possess sufficient capability to enhance maintenance approaches. Enhancements in model accuracy may be achievable with additional

Table 14. Prediction accuracy of models for residential streets

Model	Model prediction accuracy (%)				
	Pavement condition category [No. of particular segments]				
	Green [763]	Yellow [914]	Red [543]	Black [310]	Overall [2,530]
LR simple (A)	0	83	31	19	39
LR ($A+D$)	21	81	31	28	46
RF ($A+D$)	36	79	47	37	54
NN ($A+D$)	44	63	42	29	49

Table 15. Prediction accuracy of models for nonresidential streets

Model	Model prediction accuracy (%)				
	Pavement condition category [No. of particular segments]				
	Green [367]	Yellow [89]	Red [28]	Black [10]	Overall [494]
LR simple (A)	85	22	0	40	68
LR ($A+D$)	85	21	0	40	68
LR ($A+T$)	85	25	0	40	68
LR ($A+D+T$)	84	27	0	30	68
RF ($A+D$)	84	40	4	20	70
RF ($A+T$)	92	79	29	0	84
RF ($A+D+T$)	91	70	0	0	80
NN ($A+D$)	70	53	0	10	62
NN ($A+T$)	82	27	0	30	66
NN ($A+D+T$)	76	55	7	0	67

data and the incorporation of condition data obtained through automated surveys.

The RF models stand out as preferable for planning maintenance activities, but simple models could be effective in the case of limited budget and resources. Additionally, a combination of models could provide a diverse set of strategies for managing the street network. The models developed in the study are useful for optimizing maintenance schedules, improving the timing of maintenance treatments, and ultimately reducing both municipal maintenance costs and road user expenses in the long run.

For effective implementation, other municipalities would need a comprehensive pavement database and regular pavement assessments for PMS, which can be challenging due to resource constraints. Addressing these challenges would require investing in a data collection system, training personnel, and integrating new technologies for ongoing monitoring. Despite these hurdles, ML techniques can enhance resource efficiency, reduce road user costs, and improve the level of service by enabling better maintenance decisions and optimized resource allocation.

Summary and Conclusions

Predicting pavement performance is vital for timely maintenance measures, requiring quality pavement condition data and prediction models within a PMS. A precise prediction model helps the municipality optimize its intervals between maintenance treatments without the risk of an increased accident rate or vehicle damage.

This study utilizes ML to predict the PCI ratings of street pavements using manually collected subjective pavement condition data obtained from Skellefteå municipality, Sweden. The data set comprises 3,024 street pavement segments, covering a total street network of 320 km. Data sets were grouped into residential and MCI streets (nonresidential streets). Various ML models were developed, applied, and evaluated through several performance matrices and correlation measurements. The following main findings highlight several key insights regarding the performance of different models in predicting PCI ratings at the network level:

- The RF model has a better overall performance for both residential and MCI streets compared to the LR simple, LR and NN models. Similarly, the RF model consistently exhibits a greater ability to explain the variation in the data.
- The RF model based on pavement age and distress variables performed best for residential streets, while for MCI streets, the RF model utilizing pavement age and traffic variables achieved the best performance.
- Depending on the algorithm, the order of the variables based on their importance is different. However, pavement age emerges as the most significant variable for both residential and MCI street models, emphasizing the importance of maintenance history in pavement management.
- Understanding the choice of model is important for decision-making, when taking into account that the difference in performance between more advanced models and the simplest one is not substantial. It was determined that even a simple LR model could effectively predict outcomes, especially in scenarios involving manually collected pavement data or small municipalities prioritizing simplicity over accuracy due to limited maintenance budget and resources.
- Moreover, these models may be useful in improving decision-making regarding the prioritization of maintenance activities and the effective utilization of resources and budget.

Considering that the study is limited to one municipality and is based on only two pavement condition assessments conducted manually for a 4-year interval (2014 and 2018), it is recommended to increase the number of pavement condition assessments to further study the performance of ML models. Additionally, conducting similar studies in other municipalities would enhance the applicability of the ML models at the municipal level.

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Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Abambres, M., and A. Ferreira. 2017. *Application of ANN in pavement engineering: State-of-art (hal-02066889v2)*, 1–62. Coimbra, Portugal: Univ. of Coimbra.

Afridi, M. A., S. Erlingsson, and L. Sjögren. 2023. "Municipal street maintenance challenges and management practices in Sweden." *Front. Built Environ.* 9 (Sep): 1–18. https://doi.org/10.3389/fbuil.2023.1205235.

Alharbi, F. 2018. "Predicting pavement performance utilizing artificial neural network (ANN) models." Ph.D. thesis, Dept. of Civil Engineering, Iowa State Univ.

Ali, A. A., A. Milad, A. Hussein, N. I. Md Yusoff, and U. Heneash. 2023. "Predicting pavement condition index based on the utilization of machine learning techniques: A case study." *J. Road Eng.* 3 (3): 266–278. https://doi.org/10.1016/j.jreng.2023.04.002.

Al-Zou'bi, M. M., C. M. Chang, S. Nazarian, and V. Kreinovich. 2015. "Systematic statistical approach to populate missing performance data in pavement management systems." *J. Infrastruct. Syst.* 21 (4): 1–8. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000247.

Amin, M. S. R. 2015. "The pavement performance modeling: Deterministic vs. stochastic approaches." In *Numerical methods for reliability and safety assessment: Multiscale and multiphysics systems*, edited by S. Kadry and A. El Hamis, 179–196. Cham, Switzerland: Springer.

Anderson-Skold, Y., M. A. Afridi, L. Nordin, J. Patricio, A. Lindgren, C.-M. Johansson, A. Olofsson, A. Andersson, and S. Erlingsson. 2022. "Development of the SUNRA tool to improve regional and local sustainability of the transportation sector." *Sustainability* 14 (18): 1–21. https://doi.org/10.3390/su141811275.

Aranha, A. L., L. L. B. Bernucci, and K. L. Vasconcelos. 2023. "Effects of different training datasets on machine learning models for pavement performance prediction." *Transp. Res. Rec.* 2677 (8): 196–206. https://doi.org/10.1177/03611981231155902.

Cesme, B., S. Dock, R. Westrom, K. Lee, and J. A. Barrios. 2017. "Data-driven urban performance measures: Case study application in the district of Columbia." *Transp. Res. Rec.* 2605 (1): 45–53. https://doi.org/10.3141/2605-04.

CMAP (Chicago Metropolitan Agency for Planning). 2024. *Pavement data collection and pavement management system implementation for Village of Diamond, IL*, 1–38. Champaign, IL: Applied Research Associates.

Coenen, T. B. J., and A. Golroo. 2017. "A review on automated pavement distress detection methods." *Cogent Eng.* 4 (1): 1374822. https://doi.org/10.1080/23311916.2017.1374822.

Cui, L., Z. Qi, Z. Chen, F. Meng, and Y. Shi. 2015. "Pavement distress detection using random decision forests." In *Data science; Lecture notes in computer science*, edited by C. Zhang, W. Huang, Y. Shi, P. S. Yu, Y. Zhu, Y. Tian, P. Zhang, and J. He, 95–102. Cham, Switzerland: Springer.

El-Diraby, T. E., S. Kinawy, and S. M. Piryonesi. 2017. "A comprehensive review of approaches used by Ontario municipalities to develop road asset management plans." *Transportation Research Board 96th Annual Meeting Transportation Research Board*. Washington, DC: Transportation Research Board.

Erlingsson, S., and D. Saliko. 2020. "Correlating air freezing index and frost penetration depth—A case study for Sweden." In *Proc., 9th Int. Conf. on Maintenance and Rehabilitation of Pavements—Mairepav9, Lecture Notes in Civil Engineering*, edited by C. Raab, 847–857. Cham, Switzerland: Springer.

Estholm, P. 2019. *Skadeinventering asfalt Skellefteå kommun (in Swedish)*. Skellefteå, Sweden: NCC.

Farhan, J., and T. F. Fwa. 2015. "Improved imputation of missing pavement performance data using auxiliary variables." *J. Transp. Eng.* 141 (1): 1–8. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000725.

Flintsch, G. W., and K. K. McGhee. 2009. *Quality management of pavement condition data collection*. Washington, DC: National Cooperative Highway Research Program Synthesis.

Gao, L., K. Yu, and P. Lu. 2022. "Missing pavement performance data imputation using graph neural networks." *Transp. Res. Rec.* 2676 (12): 409–419. https://doi.org/10.1177/03611981221095511.

Gao, L., Y. Yu, Y. Hao Ren, and P. Lu. 2021. "Detection of pavement maintenance treatments using deep-learning network." *Transp. Res. Rec.* 2675 (9): 1434–1443. https://doi.org/10.1177/03611981211007846.

Haas, R., W. R. Hudson, and L. C. Falls. 2015. *Pavement asset management*. Hoboken, NJ: Wiley.

Haddad, A. J., G. R. Chehab, and G. A. Saad. 2022. "The use of deep neural networks for developing generic pavement rutting predictive models." *Int. J. Pavement Eng.* 23 (12): 4260–4276. https://doi.org/10.1080/10298436.2021.1942466.

Hosseini, S. A., and O. Smadi. 2021. "How prediction accuracy can affect the decision-making process in pavement management system." *Infrastructures* 6 (2): 28. https://doi.org/10.3390/infrastructures6020028.

Hu, A., Q. Bai, L. Chen, S. Meng, Q. Li, and Z. Xu. 2022. "A review on empirical methods of pavement performance modeling." *Constr. Build. Mater.* 342 (Aug): 1–17. https://doi.org/10.1016/j.conbuildmat.2022.127968.

Issa, A., H. Samaneh, and M. Ghanim. 2022. "Predicting pavement condition index using artificial neural networks approach." *Ain Shams Eng. J.* 13 (1): 101490. https://doi.org/10.1016/j.asej.2021.04.033.

Karballaeezadeh, N., H. Ghasemzadeh Tehrani, D. Mohammadzadeh Shadmehri, and S. Shamshirband. 2020. "Estimation of flexible pavement structural capacity using machine learning techniques." *Front. Struct. Civ. Eng.* 14 (5): 1083–1096. https://doi.org/10.1007/s11709-020-0654-z.

Kargah-Ostadi, N., and S. M. Stoffels. 2015. "Framework for development and comprehensive comparison of empirical pavement performance models." *J. Transp. Eng.* 141 (8): 1–7. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000779.

Kaya, O., H. Ceylan, S. Kim, D. Waid, and B. P. Moore. 2020. "Statistics and artificial intelligence-based pavement performance and remaining service life prediction models for flexible and composite pavement systems." *Transp. Res. Rec.* 2674 (10): 448–460. https://doi.org/10.1177/0361198120915889.

Kheirati, A., and A. Golroo. 2022. "Machine learning for developing a pavement condition index." *Autom. Constr.* 139 (Feb): 1–14. https://doi.org/10.1016/j.autcon.2022.104296.

Kumar, R., S. K. Suman, and G. Prakash. 2021. "Evaluation of pavement condition index using artificial neural network approach." *Transp. Dev. Econ.* 7 (2): 1–15. https://doi.org/10.1007/s40890-021-00130-7.

Laton, L. 2020. *Pavement management analysis summary report—City of Waseca*, 1–32. Tonawanda, NY: Stantec Consulting Services.

Majidifard, H., Y. Adu-Gyamfi, and W. G. Buttlar. 2020. "Deep machine learning approach to develop a new asphalt pavement condition index." *Constr. Build. Mater.* 247 (Apr): 1–19. https://doi.org/10.1016/j.conbuildmat.2020.118513.

Mallick, R. B., and T. El-Korchi. 2013. *Pavement engineering: Principles and practice*. Boca Raton, FL: CRC Press.

Marcelino, P., M. de Lurdes Antunes, E. Fortunato, and M. C. Gomes. 2021. "Machine learning approach for pavement performance prediction." *Int.*

J. Pavement Eng. 22 (3): 341–354. https://doi.org/10.1080/10298436.2019.1609673.

Martin, D. T., and R. Sen. 2023. *Austroads road deterioration model update: Cracking*, 1–33. Sydney, Australia: Austroads.

Miller, J. S., and W. Y. Bellinger. 2014. *Distress identification manual for the long-term pavement performance project*, 1–146. McLean, VA: Federal Highway Administration.

Murti, D. M. P., U. Pujianto, A. P. Wibawa, and M. I. Akbar. 2019. "K-nearest neighbor (K-NN) based missing data imputation." In *Proc., 2019 5th Int. Conf. on Science in Information Technology (ICSITech)*, 83–88. New York: IEEE.

Nabipour, N., N. Karballaeezadeh, A. Dineva, A. Mosavi, D. Mohammadzadeh, and S. Shamshirband. 2019. "Comparative analysis of machine learning models for prediction of remaining service life of flexible pavement." *Mathematics* 7 (12): 1198. https://doi.org/10.3390/math7121198.

ODOT (Ohio DOT). 2006. *Pavement conditions rating manual optimized*. Columbus, OH: ODOT.

Olowosulu, A. T., J. M. Kaura, A. A. Murana, and P. T. Adeke. 2022. "Investigating surface condition classification of flexible road pavement using data mining techniques." *Int. J. Pavement Eng.* 23 (7): 2148–2159. https://doi.org/10.1080/10298436.2020.1847285.

Piryonesi, S. M. 2019. "The application of data analytics to asset management: Deterioration and climate change adaptation in Ontario roads." Ph.D. thesis, Dept. of Civil and Mineral Engineering, Univ. of Toronto.

Ragnoli, A., M. R. De Blasiis, and A. Di Benedetto. 2018. "Pavement distress detection methods: A review." *Infrastructures* 3 (4): 58. https://doi.org/10.3390/infrastructures3040058.

Robinson, R., U. Danielson, and M. Snaith. 1998. *Road maintenance management: Concepts and systems*. London: Macmillan Education.

Sadeghi, J., E. R. Najafabadi, and M. E. Kaboli. 2017. "Development of degradation model for urban asphalt pavement." *Int. J. Pavement Eng.* 18 (8): 659–667. https://doi.org/10.1080/10298436.2015.1095912.

Sallaby, A. F., and A. Azlan. 2021. "Analysis of missing value imputation application with k-nearest neighbor (K-NN) algorithm in dataset." *Int. J. Inf. Comput. Sci.* 5 (2): 141. https://doi.org/10.30865/ijics.v5i2.3185.

Shahin, M. Y. 2005. *Pavement management for airports, roads and parking lots*. New York: Springer.

Sharma, M., and P. Kumar. 2022. "Assessment of present pavement condition using machine learning techniques." In *Road and airfield pavement technology: Lecture notes in civil engineering*, edited by H. R. Pasindu, S. Bandara, W. K. Mampearachchi, and T. F. Fwa, 71–82. Cham, Switzerland: Springer.

Sirhan, M., S. Bekhor, and A. Sidess. 2022. "Implementation of deep neural networks for pavement condition index prediction." *J. Transp. Eng. Part B: Pavements* 148 (1): 1–11. https://doi.org/10.1061/JPEODX.0000333.

Suman, S. K., and S. Sinha. 2012. "Pavement condition forecasting through artificial neural network modelling." *IJETAE* 2 (11): 474–478.

Sun, L. 2016. *Structural behavior of asphalt pavements*. Edited by L. Sun. Oxford, UK: Butterworth-Heinemann.

Trafikverket. 2011. *TRVK Väg: Trafikverkets tekniska krav Vägkonstruktion (in Swedish)*. Trafikverket.

Wågberg, L.-G. 2003. *Bära eller brista: Handbok i tillståndsbedömning av belagda gator och vägar (in Swedish)*. Stockholm, Sweden: Svenska Kommunförbundet.

Wolters, A. S., and K. A. Zimmerman. 2010. *Research of current practices in pavement performance modeling*. Harrisburg, PA: Pennsylvania DOT.

Yang, J., J. J. Lu, M. Gunaratne, and Q. Xiang. 2003. "Forecasting overall pavement condition with neural networks: Application on Florida highway network." *Transp. Res. Rec.*, 1853 (1): 3–12. https://doi.org/10.3141/1853-0101.

Zhao, B., E. Silva, and K. Soga. 2018. "Pavement degradation: A city-scale model for San Francisco, USA." *Proc. Inst. Civ. Eng. Smart Infrastruct. Constr.* 171 (3): 93–109. https://doi.org/10.1680/jsmic.18.00001.

J. Transp. Eng., Part B: Pavements, 2025, 151(2): 04025025