Quantification and Prediction of Pavement Flushing Using Surveying, Texture, and Traffic Data

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Introduction

- Flushing is shiny, black surface film of asphalt on the road surface caused by upward movement of asphalt on the pavement surface.
- This condition reduces skid resistance, especially in wet weather, and compromises pavement safety and performance.
- Current detection methods include:
  - *Manual visual inspections* – time-consuming and labor-intensive
  - *Automated image-based detection* – may yield inconsistent results.
- There is a lack of standardized and scalable methods for flushing detection and prediction.
- A need exists for a more consistent, data-driven flushing evaluation and prediction method.
- Integrating pavement texture measurements and traffic characteristics can offer a more objective, consistent, and efficient solution.

Figure 1. Example of road flushing (Highway ID: FM0020K)

Objectives

- Manually assess pavement surface images of selected roadway sections in Texas utilizing the right-of-way view.
- Establish ground truth flushing ratings referring to the TxDOT rater's manual through visual interpretation.
- Incorporate pavement surface texture metrics, specifically Mean Profile Depth (MPD), along with traffic data, to construct a comprehensive dataset for flushing analysis.
- Develop a robust predictive model capable of replicating manual flushing ratings with high accuracy and consistency.

Dataset Description

- Data sourced from TxDOT PMIS, collected annually via automated methods.
- The San Antonio district was selected as a study site for flushing distress check.
- 666 road sections analyzed manually for flushing severity.
- Dataset include:
  - ➢ *Mean Profile Depth (MPD): Minimum, maximum, mean, standard deviation, distribution,*
  - ➢ *Average Annual Daily Traffic per lane (AADT),*
  - ➢ *Equivalent Single Axle Loads per lane (ESAL),*
  - ➢ *Geographical information of Counties.*

Methodology

- Developed a predictive modeling framework to classify pavement sections into various categories of flushing (example: None, Low, Medium, and High).
- Implemented and compared the following models:
  - a) *Multiple Linear Regression* b) *Ordered Data Discrete Choice*
  - c) *Extreme Gradient Boosting* d) *Neural Network*
- The dataset was randomly split into: 80% for training and 20% for testing.

➢ Model implementation

a) Multiple Linear Regression

- To establish an interpretable relationship between flushing levels (%) and various predictor variables derived from surface texture characteristics, traffic, and related pavement information.

Flushing = β_0 + β_1·*MPD*$_{Mean}$ + β_2·*ESAL/lane* + β_3·*AADT/lane* + β_4·*Latitude* + β_5·*LatitudeDeviate* + β_6·*Pavement Type (Seal coat)* + β_7·*County_Atascosa* + β_8·*County_Bandera* + β_9·*County_Bexar* + β_{10}·*County_Comal* + β_{11}·*County_Frio* + β_{12}·*County_Guadalupe* + β_{13}·*County_Kendall* + β_{14}·*County_Kerr* + ε

b) Ordered Data Discrete Choice Model

- Investigate flushing severity categories using the DCM-based ordered model.
- Estimates cumulative probability of flushing at or below a given severity level (Figure 2).
- Model: $y^* = x'\beta + \varepsilon$
  y^* is a hidden preference among flushing class;
  x' is explanatory variables set;
  β is strength of each explanatory variable;ε is error.
- The flushing probabilities $f(\epsilon)$ are:

$Prob(y = None|x) = \Phi(-x'\beta)$

$Prob(y = Low|x) = \Phi(\mu_1 - x'\beta) - \Phi(-x'\beta)$

$Prob(y = Medium|x) = \Phi(\mu_2 - x'\beta) - \Phi(\mu_1 - x'\beta)$

$Prob(y = High|x) = 1 - \Phi(\mu_3 - x'\beta) - \Phi(\mu_2 - x'\beta)$

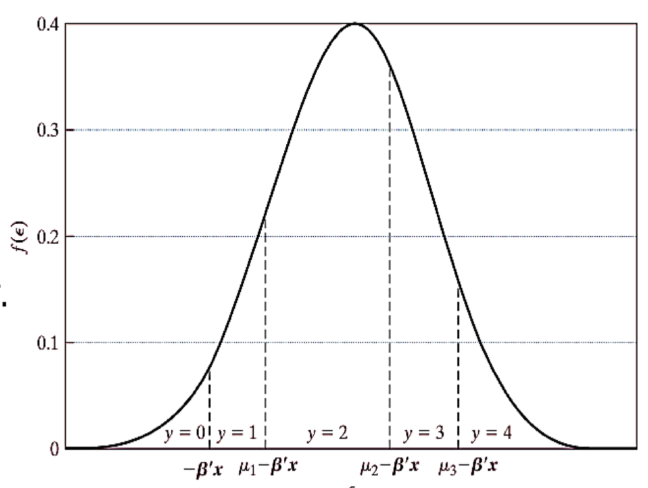

Figure 2. Probabilities in model

c) Extreme Gradient Boosting (XGBoost)

- XGBoost was used to capture complex non-linear relationships beyond the limitations of the regression and discrete choice models.
- Target variable: Flushing severity (categories)

$Objective\ function\colon L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{k=1}^{t} \Omega(f_k)$,

$Regularization\ term\colon \Omega(f) = \Upsilon T + \frac{1}{2}\lambda\, ||w||^2$

- The predicted value is updated iteratively as: $\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i)$
  where (x_i) represents the input features.

d) Neural Network Model

- A Multilayer Perceptron model was developed to classify flushing severity and the model architecture is shown in Figure 3.
- *Input layer*: *MPD*$_{Mean}$, ESAL/lane, AADT/lane, MPD distribution, Latitude, LatitudeDeviate, Pavement type, and County.
- *Hidden layer*: Captures complex, non-linear relationships; size tuned via cross-validation.
- *Output layer*: Uses the softmax function to predict probabilities for each class.

Results & Discussion

a) Multiple Linear Regression

- Flushing distress significantly varies by Pavement type (with seal coat) and County locations.
- Texture features like *MPD*$_{Mean}$ show a significant trend suggesting potential influence on flushing.

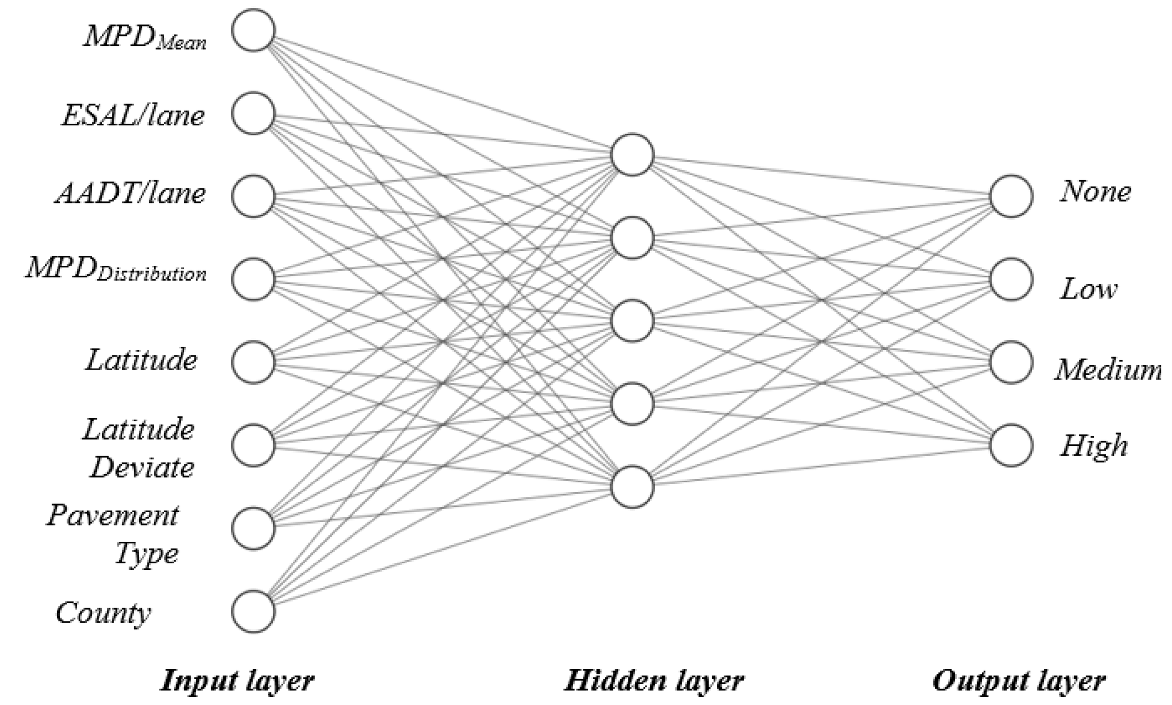

Figure 3. Architecture of Neural Network

b) Ordered Data Discrete Choice Model

- *MPD*$_{Mean}$, Pavement Type, and Counties have a significant influence on flushing.
- Training accuracy: 77.52% and testing accuracy: 77.27%.

Table 1. Ordered data discrete choice model results

Variables	Estimate	Std Error	t-value
MPD$_{Mean}$	-0.83	0.18	-4.59
ESAL/lane	0.00	0.00	0.72
AADT/lane	0.00	0.00	-0.53
Latitude	1.44	0.01	123.41
Latitude Deviate	-6.91	0.07	-92.15
Pavement Type	0.49	0.22	2.24
Atascosa	-18.83	0.24	-79.52

Variables	Estimate	Std Error	t-value
Bandera	-20.87	0.06	-358.17
Bexar	-17.62	0.02	-1081.39
Comal	-22.09	0.23	-97.21
Frio	-18.87	0.06	-301.15
Guadalupe	-20.18	0.27	-74.20
Kendall	-19.51	0.11	-181.94
Kerr	-17.96	0.21	-83.70

c) XGBoost

- Training accuracy: 99.20% and testing accuracy: 87.31%.
- Strong classification: "None" and "High" flushing levels". "Low" and "Medium" levels were not predicted since these levels are rare in the dataset.

Table 2. Confusion matrix of XGBoost model: (a) Training and (b) Testing

(a)

Class	None	Low	Medium	High
None	263	0	1	1
Low	0	10	0	0
Medium	0	0	19	0
High	2	0	0	236

(b)

Class	None	Low	Medium	High
None	63	1	2	4
Low	0	0	0	0
Medium	0	0	0	1
High	5	0	4	54

d) Neural Network Model

- Training accuracy: 87.27% and testing accuracy: 73.48%
- Strong performance for "None" and "High" flushing levels.

Table 3. Confusion matrix of Neural network model: (a) Training and (b) Testing

(a)

Class	None	Low	Medium	High
None	235	6	10	7
Low	0	0	0	0
Medium	0	0	1	0
High	32	3	10	230

(b)

Class	None	Low	Medium	High
None	45	1	0	4
Low	1	0	0	3
Medium	0	0	0	0
High	20	1	5	52

Conclusions

- Flushing severity is strongly influenced by *MPD*$_{Mean}$, Pavement Type, and County.
- The developed predictive models successfully replicate manual flushing ratings, with the highest performance for "None" and "High" severity levels.
- XGBoost gives the highest accuracy among all the models for the study dataset.
- Prediction accuracy for 'Low' and 'Medium' flushing levels is limited due to data scarcity; more balanced data would be needed to improve model performance.

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