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DATA-DRIVEN INSPECTION PLANNING FOR UTAH CULVERTS USING FEDERATED LEARNING

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16. Abstract

In recent years, transportation agencies have increasingly turned to machine learning (ML) to enhance the effectiveness of infrastructure asset management. However, limited local inventory data often hinders building accurate and reliable ML models. Additionally, data privacy and ownership concerns discourage agencies from sharing raw datasets. Many state departments of transportation (DOTs), including the Utah DOT (UDOT), face challenges in managing culverts due to limited inspection data and privacy concerns. This research proposes using federated learning (FL), an emerging ML paradigm, to enhance culvert condition prediction without requiring centralized data sharing. By leveraging FL, UDOT can collaboratively train predictive models with data from other state DOTs while preserving data confidentiality. The project involves collecting culvert and environmental data from multiple state inventories, preprocessing them to ensure consistency, and developing artificial neural network (ANN)-based models within the FL framework. The resulting FL model achieved an accuracy of 80.4%, performing comparably to the centralized model trained on the fused dataset and significantly outperforming the model trained solely on Utah's data. The findings demonstrate that FL can effectively support high-performance predictive modeling while preserving data. This research offers a novel approach to infrastructure asset management that balances predictive accuracy with regulatory compliance, setting a precedent for broader adoption of FL in transportation systems.

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Data-Driven Inspection Planning for Utah Culverts Using Federated Learning

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ABSTRACT

In recent years, transportation agencies have increasingly turned to machine learning (ML) to enhance the effectiveness of infrastructure asset management. However, limited local inventory data often hinders building accurate and reliable ML models. Additionally, data privacy and ownership concerns discourage agencies from sharing raw datasets. Many state departments of transportation (DOTs), including the Utah DOT (UDOT), face challenges in managing culverts due to limited inspection data and privacy concerns. This research proposes using federated learning (FL), an emerging ML paradigm, to enhance culvert condition prediction without requiring centralized data sharing. By leveraging FL, UDOT can collaboratively train predictive models with data from other state DOTs while preserving data confidentiality. The project involves collecting culvert and environmental data from multiple state inventories, preprocessing them to ensure consistency, and developing artificial neural network (ANN)-based models within the FL framework. The resulting FL model achieved an accuracy of 80.4%, performing comparably to the centralized model trained on the fused dataset and significantly outperforming the model trained solely on Utah's data. The findings demonstrate that FL can effectively support high-performance predictive modeling while preserving data. This research offers a novel approach to infrastructure asset management that balances predictive accuracy with regulatory compliance, setting a precedent for broader adoption of FL in transportation systems.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

The Utah Department of Transportation (UDOT) faces significant challenges in managing over 47,000 culverts across the state, due primarily to sparse inspection records and data scarcity. One effective approach to improving traditional culvert inspection and management is leveraging the capabilities of artificial intelligence, including machine learning (ML). Traditional ML approaches for culvert condition prediction require large, diverse datasets, something UDOT currently lacks. To address this, the research project explored federated learning (FL) as an innovative, privacy-preserving solution for predictive culvert maintenance.

This study developed and evaluated an FL framework that enables collaborative model training across multiple state departments of transportation (DOTs) without exchanging raw data. Using inspection records from six states, including Utah, the research team trained predictive models to estimate culvert condition ratings. These models incorporated both physical features (e.g., material, length) and environmental factors (e.g., soil pH, flooding frequency) and were implemented using artificial neural networks (ANNs) within the FL framework.

Four models were tested: a local Utah model (Utah-CL), a synthetic data-augmented model (Utah-SMOTE), a centralized model using all state data (ALL-CL), and the proposed FL model (ALL-FL). The FL model outperformed both local and synthetic approaches and achieved performance comparable to the centralized model, attaining 96% of the centralized model's accuracy while ensuring data privacy. It also excelled in identifying high-risk culverts, achieving notably higher precision and recall rates for critical condition classes.

The findings confirm the feasibility of FL for culvert condition prediction under data-limited scenarios. Moreover, FL proved to be a scalable and effective alternative to data augmentation, offering UDOT a practical solution to prioritize inspections, allocate maintenance budgets strategically, and improve safety outcomes. By implementing the FL framework into its asset management systems, UDOT can enhance decision-making while collaborating with other DOTs without breaching data privacy regulations.

1. INTRODUCTION

1.1 Project Motivation

Managing and maintaining critical transportation infrastructure components, such as culverts, are associated with significant challenges that directly impact public safety and economic efficiency. Culverts, serving as conduits under roadways and railways for water flow (Figure 1), are susceptible to deterioration over time due to factors like weather conditions, material wear, and load stresses (Salem, Salman, and Najafi 2012). The failure to address the deteriorating condition of culverts in a timely manner can lead to severe consequences, including roadway collapses, flooding, environmental damage, and costly emergency repairs. To mitigate these risks and ensure the long-term functionality of the transportation network, a systematic approach to culvert condition assessment and maintenance is paramount (Mohammadi, Rashidi, et al. 2023). Unfortunately, traditional culvert inspection and management practices are no longer appropriate to meet the growing demands of modern infrastructure networks due to their reactive nature, high labor costs, and the disruption they cause to traffic flow (Piratla, Jin, and Yazdekhasti 2019).

Figure 1. Culvert under a road

A strategy to enhance traditional culvert inspection and management practices lies in employing the power of artificial intelligence. Specifically, innovative machine learning (ML) algorithms have opened up fresh avenues for creating more efficient and powerful strategies for inspecting and managing culverts (Stoner, Pang, and Piratla 2019). ML algorithms are capable of making accurate predictions. By analyzing historical inspection data, weather patterns, and environmental factors, ML models can predict the likelihood of culvert deterioration. This predictive capability enables a proactive approach for maintenance, allowing agencies to prioritize repairs before critical failures occur, minimizing disruptions, and optimizing resource allocation (Meegoda et al. 2017).

While data-driven approaches like condition prediction models offer the potential to transform infrastructure asset management, many DOTs face a major obstacle: data scarcity. This lack of sufficient data can stem from several factors, including the high cost and resource demands of traditional data collection methods and the absence of a centralized data management system (Sinha, Labi, and Agbelie 2017). These data collection methods often rely on manual inspections, which require significant labor hours, specialized equipment, and transportation resources to access and evaluate infrastructure assets such as culverts. For example, the Utah Department of Transportation (UDOT) lacks a comprehensive culvert management system. This results in sparse and inconsistent inspection records for its extensive culvert inventory with more than 47,000 culverts across the state, hindering the development of robust predictive models (Mohammadi, Sherafat, et al. 2023; Beaver and McGrath 2005).

1.2 Research, Objectives, and Tasks

Data scarcity is a significant challenge for UDOT as it seeks to leverage predictive models for culvert asset management. The lack of comprehensive, high-quality data directly impedes the development and effectiveness of ML models, which rely on large, diverse datasets to make accurate predictions. Insufficient data results in reduced model accuracy, as the available training sets are too small or unrepresentative to provide reliable insights into the condition of infrastructure assets like culverts. This limitation restricts the application of advanced ML techniques and increases the risk of overfitting, where a model performs well on training data but fails to generalize to new or unseen data (Mohammadi, Rashidi, and Asgari 2024c).

The scarcity of data in the context of culvert asset management complicates the identification of critical patterns, predicting asset deterioration, and prioritizing maintenance activities. To overcome these challenges and fully utilize the potential of ML in managing culverts, a variety of strategic methods are required. These include improving data collection techniques, such as adopting more automated and efficient sensing technologies, integrating data from other transportation agencies, and optimizing the use of existing data through advanced analytics (Gillani and Niaz 2023).

One of the most effective methods for addressing data scarcity is collaborative data sharing among different state DOTs. By merging inventory data from other agencies, UDOT can significantly enhance the diversity and richness of its datasets. This approach allows for a more comprehensive view of the demands and usage patterns of culverts, increasing the robustness and accuracy of predictive models (Mohammadi, Rashidi, and Asgari 2024b). For instance, data from other DOTs can help fill gaps in UDOT's own dataset, providing valuable insights into regional variations in infrastructure health and enabling the creation of more generalized models applicable across various geographic areas. However, this strategy faces a number of significant challenges that need to be addressed before it can be fully realized.

First, inconsistent data formats and protocols across DOTs present a major barrier to the seamless merging of datasets. Each agency may use different standards for data collection, storage, and reporting, which makes it difficult to standardize and integrate data from multiple sources. Second, data privacy regulations such as the General Data Protection Regulation (GDPR) (Voigt and von dem Bussche 2017) and the California Consumer Privacy Act (CCPA) (Bukaty 2019) impose stringent limitations on data sharing, especially when it comes to personal or sensitive information. These regulations are designed to protect the privacy of individuals and organizations, but they can complicate data sharing across jurisdictions. Finally, reluctance among some DOTs to share data due to competitive interests or administrative obstacles is another critical issue.

Researchers facing the challenges of limited infrastructure data and data-sharing obstacles have found a promising solution in federated learning (FL). This innovative ML technique, pioneered by Google in 2016 (Konečný et al. 2016), was designed specifically to address data privacy and scarcity concerns. This was initially built to enhance text prediction across Android devices while complying with privacy regulations like GDPR and CCPA. The key to FL lies in its collaborative yet decentralized structure. This enables collective learning without compromising the privacy of individual data sources (McMahan et al. 2017).

While previous studies have shown the promise of FL in various fields, its potential for infrastructure management with limited data remain underexplored (Mohammadi, Rashidi, and Asgari 2024a). This research investigates the effectiveness of FL for predictive analysis in this context, specifically for UDOT's culvert inspection planning. The proposed FL method allows UDOT to benefit from data held by other state DOTs while maintaining strict data privacy and security. This research aims to showcase FL's potential for culvert condition prediction models, providing valuable insights for UDOT and other DOTs facing data scarcity and data privacy concerns. The objective of this research project is threefold:

1) Assess the feasibility of FL for culvert condition prediction with limited data
2) Evaluate the performance of FL models compared to traditional centralized ML models
3) Quantify the privacy benefits of FL for UDOT

To achieve our objectives, the following section will review existing culvert condition prediction models and explore the application of FL in academic literature. Subsequently, we will discuss the data collection and preparation process and the development of FL and ML models. Finally, we will elaborate on this study's outputs and key findings.

1.3 Report Overview

This report is organized into the following key sections:

- **Introduction**: This section outlines the motivation behind the research, detailing the challenges faced by UDOT in managing culvert inspections and the role of ML in addressing these issues. It also defines the research objectives and tasks.
- **Background**: This section reviews existing ML applications in culvert inspection and the introduction of FL as a solution to data privacy concerns in collaborative data sharing across state DOTs.
- **Methodology**: This section describes the process of data collection and preparation, model development using ANN, and the implementation of FL to overcome data limitations.
- **Results and Discussion**: The findings from applying FL to culvert condition prediction are presented and analyzed. This section compares FL with traditional ML models and discusses the advantages of using FL, particularly in terms of accuracy and data privacy.
- **Conclusions and Recommendations**: The final section summarizes the study's key findings and provides recommendations for future research and practical applications of FL in infrastructure management.

Following this structure, the report effectively presents the background, methodology, results, and implications of using FL to enhance culvert condition prediction while preserving data privacy.

2. BACKGROUND

In this section, we review the literature regarding the applications of ML to enhance culvert inspection processes. Also, we discuss existing FL deployment and its potential application within the context of culvert condition prediction models.

2.1 ML Applications in Culvert Inspection

The condition of a culvert, typically represented by a numerical value, is determined by a combination of factors that affect its structural integrity and performance. Given the numerous variables that influence the condition of a culvert, its assessment is a complex task (L. Li et al. 2020). Researchers have increasingly turned to ML techniques, which have proven effective in addressing complex challenges. The development of ML-driven models for predicting culvert conditions has significantly enhanced traditional inspection approaches, offering more accurate insights and predictions (T. Li, Sahu, Zaheer, et al. 2020). Table 1 provides a summary of the different models developed in this field. These predictive models enable DOTs to better estimate the rate of culvert degradation, facilitating more targeted inspection schedules based on the predicted condition. By prioritizing inspections for the most vulnerable culverts, these models help to extend their operational lifespan and ensure a safer, more reliable infrastructure.

For example, Tran et al. (2006) introduced a probabilistic neural network (PNN) model to classify and estimate the deterioration of pipes. Their study involved a discriminant analysis, comparing the performance of the PNN with that of a traditional parametric model. This comparison highlighted nine critical factors that influence concrete stormwater pipe deterioration, with the PNN model performing slightly better in terms of predictive accuracy. The dataset used for training the models was drawn from the City of Greater Dandenong, Australia, and contained only 583 data points, a limitation that constrained the robustness of the model. Another study by Salem et al. [(2012)] identified key factors contributing to the deterioration of metal culverts. They built a deterioration prediction model based on a relatively small dataset of 99 records from the Ohio DOT using a binary logistic regression model and forward stepwise variable selection. However, this study was also limited by its narrow dataset, which included just four independent features. While offering valuable insights, both studies focused on specific types of pipes, which restricts the broader applicability of their findings.

Further progress was made by Tatari et al. (2013), who developed a regression model using ANNs to predict culvert conditions based on Ohio DOT's culvert inventory data. This model, which incorporated nine features such as traffic data, culvert type, and age, was trained on a small sample of just 39 culverts, leading to an inherently high feature-to-data ratio. Meanwhile, Stoner et al. (2019) leveraged a large dataset of 8,000 culverts from South Carolina DOT to create predictive models using ANNs and logistic regression. They constructed individual models for each of the six types of culverts in the state, using a comprehensive dataset that included 10 defect categories. Their approach utilized a multiclass classification algorithm and successfully predicted culvert conditions across various ages. However, this study was limited to data from one state, and its findings might not apply to other regions with differing culvert conditions.

In recent years, additional studies have focused on improving ML-based culvert condition prediction models. Gao and Elzarka (2021) developed a binary classification model using a decision tree algorithm to assess the condition of culverts in Ohio. This model, which used 11 features from the ODOT culvert dataset, achieved a 75% accuracy rate. While the model performed well, its binary nature, classifying culverts into only two condition categories, was a notable limitation. Moreover, the data used in this study were sourced solely from Ohio, which restricts its generalizability to other states. In a more comprehensive study, Mohammadi et al. (2023) compared five multiclass classification algorithms (random forest, decision tree, support vector machine, k-nearest neighbors, and ANN) for predicting culvert condition ratings. Their study, which incorporated a diverse dataset of 2,555 culvert records from four states, showed that the random forest (RF) algorithm outperformed the others in terms of accuracy, precision, recall, and F1 score. However, the study faced challenges with data privacy compliance since it combined data from multiple states, which may have violated privacy regulations.

Table 1. A summary of studies that developed ML models for culvert inspection programs

Reference	Year	Objective
Tran et al. (2009)	2009	Predicting the structural condition of pipes with PNN
Salem et al. (2012)	2012	Predicting the binary scale of culvert condition with logistic regression
Tatari et al. (2013)	2013	Predicting the adjusted overall rating of culverts' condition with ANN
Stoner et al. (2019)	2016	Predicting culvert condition ratings with ANN and logistic regression
Gao and Elzarka (2021)	2021	Predicting the binary scale of culvert condition with a decision tree
Mohammadi et al. (2023)	2023	Predicting culvert condition ratings with RF, SVM, decision tree, ANN, and k-nearest neighbor

2.2 Federated Learning Applications

FL introduces a revolutionary approach to data analysis and the development of ML models by overcoming the legal and privacy restrictions typically associated with data fusion. Instead of centralizing datasets, FL operates in a decentralized manner, making it an ideal solution for sensitive data management. Several pioneering studies have acknowledged FL's importance and explored its application in various real-world scenarios. This literature review section focuses on using FL in the civil engineering sector.

In one such study, Khalil et al. (2022) applied FL to maintain privacy in ML, specifically for predicting the thermal comfort of workers in industrial IoT environments. They developed a federated neural network algorithm, named Fed-NN, which not only preserved privacy but also cut communication overhead by 50%. Their experiments demonstrated that Fed-NN could forecast thermal comfort with 80% accuracy while ensuring privacy in industrial IoT settings. Similarly, Moretti et al. (2021) proposed a federated model designed to enhance digital twin (DT) applications. By employing a cross-disciplinary and multiscale approach, they successfully built a federated data model to support DT-based asset management tools. This model was validated with a federated building-level DT for the West Cambridge Campus, showcasing its potential for real-time applications at both building and environmental scales.

In construction management, FL offers significant potential for fostering collaboration and enhancing data sharing. Zhang and Pan (2022) developed an FL-based collaboration framework aimed at overcoming challenges in the intelligent design of residential buildings. This framework leveraged FL to train ANN models directly on the data owners' local devices, ensuring that sensitive building drawings are not shared. To encourage data sharing, the framework incorporates a collaboration matching mechanism based on game theory. This mechanism rewards data owners who contribute higher-quality and larger quantities of data by granting them access to more data in return. The case study involving residential building drawings demonstrated that the ANN model trained via FL on a larger, aggregated dataset outperformed the model trained on local data alone, highlighting the advantages of this collaborative approach. Li et al. (2021) also employed FL to tackle privacy concerns in construction worker data and address the challenge of preserving the personalization of safety monitoring systems. They introduced FedSWP, a framework utilizing federated transfer learning to protect personal image data while enhancing the accuracy of occupational health and safety (OHS) monitoring systems. Their model demonstrated its ability to provide accurate safety alerts and health recommendations, particularly for crane operators monitoring facial fatigue. Using FL, they significantly improved model performance, showcasing the scalability of FedSWP in diverse construction OHS applications.

FL is also finding significant applications in transportation systems, where large volumes of data are generated by various sources, including vehicles, sensors, and infrastructure. These data often contain sensitive information related to travel patterns and locations, making privacy preservation a crucial consideration. Alqubaysi et al. (2025) proposed an FL-based predictive traffic management (FLPTM) system to optimize service access and privacy for autonomous vehicles (AVs) within an ITS. The system employed a contained privacy-preserving scheme (CPPS) that decentralizes data processing, enabling vehicles to train local models while keeping raw data confidential. The FLPTM system showed promising results in reducing communication costs, mitigating adversarial effects, and improving access time while maintaining data privacy. In a similar application, Saputra et al. (2019) developed an FL-based approach to predict energy demand in electric vehicle networks. Their method improved the prediction accuracy while minimizing communication overhead and preserving user privacy. Anaissi et al. (2023) leveraged FL for structural health monitoring, applying a personalized FL approach to overcome non-IID data challenges in FL. Their model, based on a deep neural network and autoencoder architecture, achieved impressive damage detection accuracy (86% to 97%) compared with traditional FL methods.

Despite these advances, there remains a gap in addressing the data scarcity in culvert inventories, a challenge that many transportation agencies, including UDOT, face. Previous studies on condition assessment of culverts have encountered several limitations, such as using data from a single state's culvert inventory (Tatari et al. 2013; H. D. Tran, Perera, and Ng 2009; Stoner, Pang, and Piratla 2019) and primarily employing binary classification models (Gao and Elzarka 2021; Salem, Salman, and Najafi 2012). To address these issues, we propose a comprehensive FL-based model designed to handle data inconsistencies and noise without significant loss in performance. This model's strength lies in its ability to generalize to new, unseen data beyond just the datasets on which it was trained. It aims to enhance culvert condition prediction models while addressing privacy concerns and maintaining compliance with data protection regulations. Additionally, we conducted a comparative analysis between traditional data augmentation techniques and FL, demonstrating FL's superior ability to handle data scarcity compared with other leading solutions.

3. METHODOLOGY

The primary focus of our research is to address data scarcity within UDOT's culvert inventory while maintaining data privacy. With many culvert inspection records being missed in Utah's culvert inventory, the resulting gap poses a serious challenge for sound decision-making regarding culvert inspection and maintenance. To overcome this data scarcity, we considered two approaches:

1) Sourcing culvert data from other DOT inventories to create a richer and more informative dataset
2) Augmenting the dataset with synthetic data using the Synthetic Minority Oversampling Technique (SMOTE)

Traditionally, when data are gathered from multiple datasets or organizations, the standard approach has been to utilize centralized ML models. However, data privacy has been a significant concern with this method (Mohammadi, Rashidi, and Asgari 2024b). In light of the growing global focus on data privacy and the risks associated with centralized learning, we propose an alternative solution, FL, that balances leveraging comprehensive datasets and ensuring data privacy (Figure 2). Additionally, we suggest implementing an ANN as the ML algorithm within the FL framework. To assess the effectiveness of this approach, our study compares the performance of the developed ML models under various scenarios.

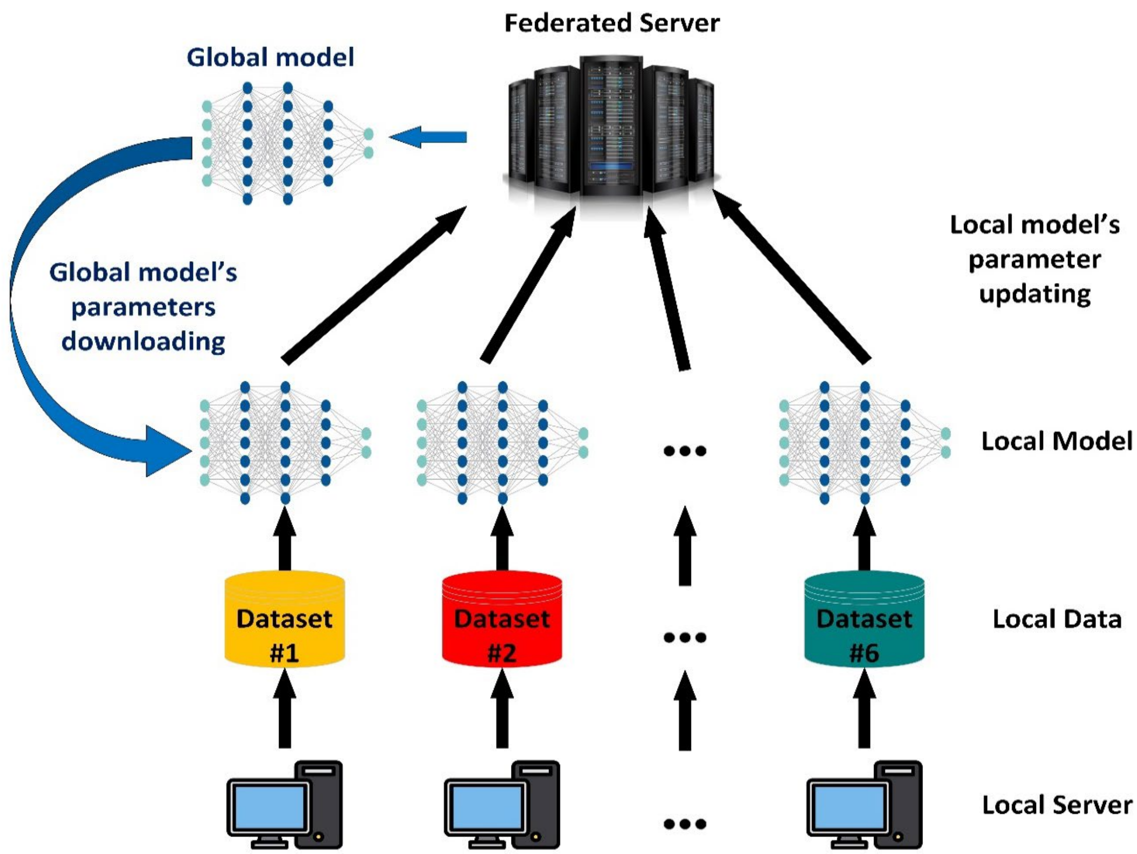

Figure 2. The proposed model for predicting Utah culvert conditions based on FL

3.1 Data Collection and Preparation

To address the data scarcity in Utah's culvert inspection records, we extended our data collection to include culvert inventories from five additional states: Colorado, Vermont, New York, Massachusetts, and Ohio. These states contributed the following number of culvert records: 766 from Colorado, 3,884 from Vermont, 1,050 from New York, 417 from Massachusetts, and 1,851 from Ohio. Since these states' DOTs have made their culvert data publicly available, we accessed these datasets through ArcGIS websites and open data portals. These states were selected based on their data availability and the similarity of their culvert features to those in Utah. Key similarities included the presence of essential physical attributes in the culvert inventories, such as structure type, shape, length, year of installation, and inspection dates. Any inventories missing these key characteristics were excluded from the analysis. Furthermore, the inspection protocols followed by these states often adhered to, or were adaptations of, the National Association of Sewer Service Companies (NASSCO 2001) guideline. This guideline established a common framework for assessing pipe or culvert conditions and facilitated data preprocessing.

However, note that the inspection data from these states did not follow a standardized manual. To resolve this issue, we applied a data preprocessing method. This preprocessing approach is analogous to data preprocessing in centralized learning. Key steps involved adjusting categorical features to ensure consistency across datasets and standardizing target labels. Specifically, we standardized the culvert rating scales (target labels) from the different states to match Utah's 5-point rating system. This required converting the 9-point scale used by Colorado DOT, Vermont's 7-point scale, Ohio DOT's 9-point scale, New York DOT's 7-point scale, and Massachusetts DOT's 10-point scale to align with UDOT's rating system. To ensure the conversion was accurate, we conducted a thorough analysis comparing the inspection criteria of these states with UDOT's standards. Refer to Table 2 for a detailed explanation of how each state's rating scale was mapped to UDOT's system.

Table 2. Rating scales standardization

UDOT	Minor Defects (5)	Moderate Defects (4)	Significant Defects (3)	Major Defects (2)	Critical Defects (1)
CDOT & ODOT	9 & 8	7	6	4 & 5	1 & 2 & 3
VTrans	Excellent	Good & Fair	Poor	Critical	Urgent & Closed
NYSDOT	7	6 & 5	4	3	0 & 1 & 2
MASSDOT	9 & 8	7	6	5	0 & 1 & 2 & 3 & 4

The final dataset used to develop the ML models comprised inspection data for 8,240 culverts sourced from the inventory databases of six different states. This dataset was divided into two main categories of variables: physical features, which were directly available in the inventories, and environmental features, which were added to enrich the data. The physical features included key culvert properties such as material, shape, length, installation year, inspection year, and geographic coordinates (longitude and latitude). These structural and historical details were directly extracted from each state's culvert inventory databases.

In addition to the physical features, we supplemented the dataset with environmental features that were not initially included in the culvert inventories. Specifically, soil-related properties, such as soil pH, drainage class, moisture content, electrical conductivity, and flooding frequency, were collected from the USDA's Web Soil Survey database (Soil Survey Staff, Natural Resources Conservation Service n.d.). Using ArcGIS, we extracted and compiled the soil data before integrating those data with the culvert records. By incorporating these environmental factors, we enriched the multi-state inspection data, creating a more comprehensive feature set for building ML models that can generalize across diverse geographical regions. After completing the data preprocessing, the final set of variables used for model development is presented in Table 3.

Table 3. Variables considered for the model development

<table>
<tr><th colspan="2">Variables</th><th>Target Label</th></tr>
<tr><td rowspan="5">Environmental features</td><td>Soil pH</td><td rowspan="10">Culvert condition rating</td></tr>
<tr><td>Soil drainage class</td></tr>
<tr><td>Soil moisture</td></tr>
<tr><td>Soil electrical conductivity</td></tr>
<tr><td>Flooding frequency</td></tr>
<tr><td rowspan="5">Physical features</td><td>Culvert installation year</td></tr>
<tr><td>Culvert structure</td></tr>
<tr><td>Culvert shape</td></tr>
<tr><td>Culvert length</td></tr>
<tr><td>Culvert inspection date</td></tr>
</table>

3.2 Model Development

To address the challenge of limited data availability in UDOT's culvert dataset, we proposed leveraging FL as a strategic solution. FL enables multiple agencies or regions to collaboratively train ML models without the need to exchange raw data, thereby preserving data privacy while expanding the effective training dataset. To demonstrate the efficacy of this approach, we plan to develop and compare four ML models: three centralized models built using ANNs trained on a single or fused dataset, and one federated model that distributes training across decentralized nodes. This comparison will allow us to evaluate the performance gains and practical benefits of FL in addressing data scarcity while maintaining privacy standards.

3.2.1 Artificial Neural Network (ANN)

ANN is an ML algorithm inspired by the structure and function of the human brain, designed to replicate the communication processes between biological neurons. ANNs consist of interconnected nodes, known as artificial neurons, organized in a layered structure. Typically, an ANN includes an input layer, multiple hidden layers, and an output layer, as shown in Figure 3. Each connection between neurons is assigned a weight that determines the influence of one node on another. These weights are updated during the model's training process to produce accurate outputs (Mohammadi, Rashidi, et al. 2023; Hassandokht Mashhadi, Rashidi, and Marković 2024). The core operation of a neuron is based on a weighted sum of its inputs, which is then passed through an activation function. This can be expressed mathematically as:

$$y_i = f\left(\sum_i \omega_i x_i\right)$$

Here, y_i represents the output vector, $x_i \in R^d$ is the input vector with d dimensions of features, $\omega_i \in R^d$ is the model's parameter vector (including weights and biases), and f denotes the activation function. By using activation functions such as sigmoid, tanh, or ReLU, non-linearity is introduced into the model, allowing it to capture complex patterns in data (J. Li et al. 2022).

ANNs have proven highly effective in modeling intricate relationships with minimal programming and have been widely applied in civil engineering. Notable applications include predicting formwork pressure in self-compacting concrete, estimating work zone capacities, and forecasting the lateral capacity of monopiles (Gamil et al. 2023; Mashhadi, Markovic, and Rashidi 2022; Taherkhani, Amir Hosein, Mei, and Fei 2023). The ANN architecture employed in this study for model development is illustrated in Figure 3. To improve the model's capacity to learn complex non-linear relationships, we incorporated the ReLU activation function between layers. The model's parameter vector (ω) was optimized by fitting the output (y_i) to the cross-entropy loss function ($\ell(.,.)$). The objective function for the multi-class classification ANN model developed in this study is represented as follows:

$$\mathbf{argmin}_{\omega \in R^d} \mathcal{L}(\omega) = \sum_{i}^{n} \ell(f(x_i), y_i)$$

Where i^{th} data sample is part of the dataset D, which consists of n data points.

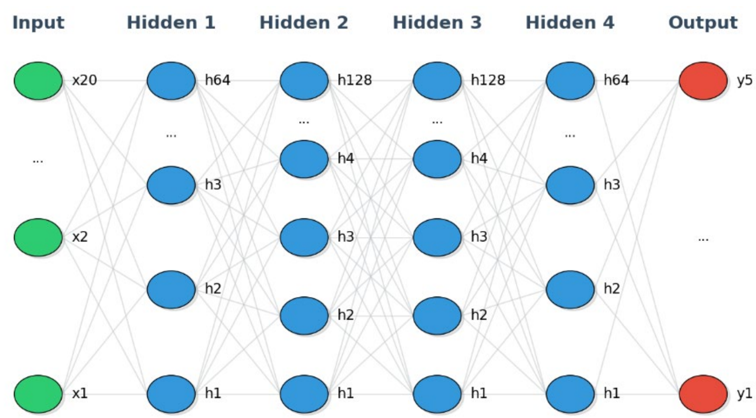

Figure 3. The developed ANN's architecture

3.2.2 Federated Learning (FL)

FL represents a modern shift in ML, enabling distributed collaboration among multiple participants. Rather than exchanging raw data, each participant trains a model on its own dataset and shares only the learned parameters. These updates are then aggregated to form a comprehensive global model (T. Li, Sahu, Talwalkar, et al. 2020). This method supports various ML techniques, including but not limited to decision trees, logistic regression, and ANNs. In this research, we employed ANNs due to their high effectiveness in prediction tasks, suitability for multiclass problems, and seamless integration with the Flower framework. Flower is an open-source platform designed specifically to support federated systems, allowing customization through different algorithms and optimization techniques (Beutel et al. 2020). Our choice of ANNs within this ecosystem was reinforced by their proven performance across numerous academic studies (Goto et al. 2023; Senapati et al. 2023).

When analyzing FL more deeply, it can be classified based on how the data are distributed among participants. There are three primary types: horizontal FL, vertical FL, and federated transfer learning (FTL). Horizontal FL, also known as data parallelism, is applied when all participants possess the same set of features but work with different samples. A common use case might involve smartphones collecting keyboard data from different users to improve next-word prediction models. Each client uses the same model architecture and training parameters. This setup improves generalization by learning from diverse data while ensuring privacy by keeping personal information on-device. Conversely, vertical FL arises when participants have different features but share data samples. For example, one organization may collect demographic information while another holds purchasing records for the same individuals. This arrangement allows models to benefit from complementary feature sets while upholding privacy by separating the data attributes. Lastly, FTL is used when there is both feature and sample heterogeneity. This method typically involves using a model pre-trained on a related task, which is then fine-tuned locally at each node, such as IoT devices or smartphones. This approach offers quicker training times, eliminates the need to start from scratch, and provides customization based on localized datasets (L. Li et al. 2020; Yang et al. 2019). In our study, since DOTs maintain similar data structures but differ in the records they collect, we adopted horizontal FL as the most appropriate model.

The neural network structure and the loss function employed within the FL setup mirrored those used in the centralized ML models to ensure consistency in comparison. For the FL implementation, we adopted Federated Averaging (FedAvg) as our foundational algorithm, detailed in Algorithm 1. FedAvg is widely recognized for its straightforward design and strong performance in aggregating model updates across multiple distributed participants (L. Li et al. 2020). The process begins with a central coordinator initializing a global model (ω_0) and sharing it with a randomly selected group of participating clients (S_t). Each client then trains the model using its own private dataset (D_n), and upon completion, returns the updated parameters (ω_t^n) along with the number of local training samples. The server then updates the global model (ω_{t+1}) by computing a weighted average of the local contributions, factoring in the size of each client's dataset. This newly updated model is redistributed for the next training iteration. The training cycle continues until the model achieves satisfactory performance. This method ensures that each client's influence on the global model is proportional to the volume of data it holds, enabling balanced and privacy-preserving learning across the network.

To evaluate the performance of our ML models on unseen data, we adopted a hold-out cross-validation approach. This technique involves splitting the dataset into two separate portions: one for model training and the other for testing its generalization ability (Mohammadi et al. 2025). Specifically, we allocated 80% of the data for training and the remaining 20% for testing. In the centralized learning setup, this process occurs in a unified environment where the entire model is trained and validated in a single location. However, implementing hold-out cross-validation in an FL context requires modifications due to the decentralized nature of training. In FL, each participant retains a portion of their local data for testing and uses the rest to train the shared model. Once local evaluations are completed, performance metrics such as accuracy and precision are collected from each agent and averaged to estimate the overall effectiveness of the global model. A detailed overview of the key steps and logic behind our FL setup is provided in the accompanying pseudo-code.

Algorithm 1: Federated Averaging Algorithm (FedAvg)

Input: Number of agents (N), Local datasets (D_n), the strategy of the framework, including the number of communication rounds (m), the fraction of agents on each round (s), the number of local epochs (E), learning rate (η), optimization function ($Adam$), and local mini-batch size (B).

Output: updated parameters of global ANN model (ω), ANN model's performance metrics (p)

Server Execution:

Initialize global neural network model (ω_0)

for round t = 1, 2, …, m **do**

  $S_t \leftarrow$ random subset of $max(\text{s} \times \text{N}, 1)$ branches to participate in the training

  Distribute ω_0 to all agents in S_t

  for each agent $D_n \in S_t$ **in parallel do**

    Initialize $\omega_t^n = \omega_0$

    $\omega_{t+1}^n, p_t^n \leftarrow$ Agent_Update (D_n, ω_t^n)

  end

  $\omega_{t+1} \leftarrow \frac{1}{|\{S_t\}|} \sum_{D_n \in S_t} \omega_{t+1}^n$

  $p_t \leftarrow \sum_{D_n \in S_t} \frac{|D_n|}{\sum_{D_n \in S_t} |D_n|} \times p_t^n$

end

Agent Execution:

Agent_Update $(\mathrm{D_n}, \omega)$:

$D_n^{train}, D_n^{test} \leftarrow$ Split D_n $into\ train\ and\ test\ sets$

for epoch e = 1, 2, …, E **do**

  $\mathcal{B}^{train} \leftarrow$ Split $\mathrm{D_n^{train}}$ into batches of size B

  for batch $b \in B^{train}$ **do**

    $\omega \leftarrow \omega - \eta\big(Adam(\omega; b)\big)$

  end

end

$\mathcal{B}^{test} \leftarrow$ Split D_n^{test} into batches of size B

for batch $b \in B^{test}$ **do**

  $p_b \leftarrow$ calculate the model's performance on the agent's test set

end

$p \leftarrow \sum_{b \in B^{test}} \frac{|b|}{|B^{test}|} \times p_b$

return ω, p to server

4. RESULTS AND DISCUSSION

Recent advancements in artificial intelligence have sparked growing interest among transportation departments in integrating these tools, particularly predictive ML models, into their infrastructure asset management workflows. Despite this enthusiasm, the implementation of ML has been hindered by data limitations and concerns surrounding data confidentiality. To navigate these challenges, our study explored using FL as a decentralized solution for building predictive models targeting infrastructure condition assessment. We applied this method to culvert inspection practices in Utah, where the available dataset was insufficient in size and coverage. To overcome this limitation, we incorporated culvert data from other state DOTs using the FL approach, which enabled collaborative training without compromising data privacy. To benchmark the performance of FL, we also developed three centralized ANN-based models: Utah-CL (trained solely on Utah's dataset), Utah-SMOTE (trained on Utah's data augmented with synthetic samples), and ALL-CL (trained on a fused dataset from six states). We evaluated all models using standard performance indicators such as accuracy, precision, recall, F1 score, and total loss. As illustrated in Figure 4, the federated model (ALL-FL) consistently outperformed both Utah-CL and Utah-SMOTE across all metrics, achieving a 30.4% improvement in accuracy over Utah-CL. Although the centralized ALL-CL model achieved the highest accuracy, the ALL-FL model followed closely, attaining approximately 96% of its performance, highlighting FL's strong viability and promise in transportation infrastructure analytics.

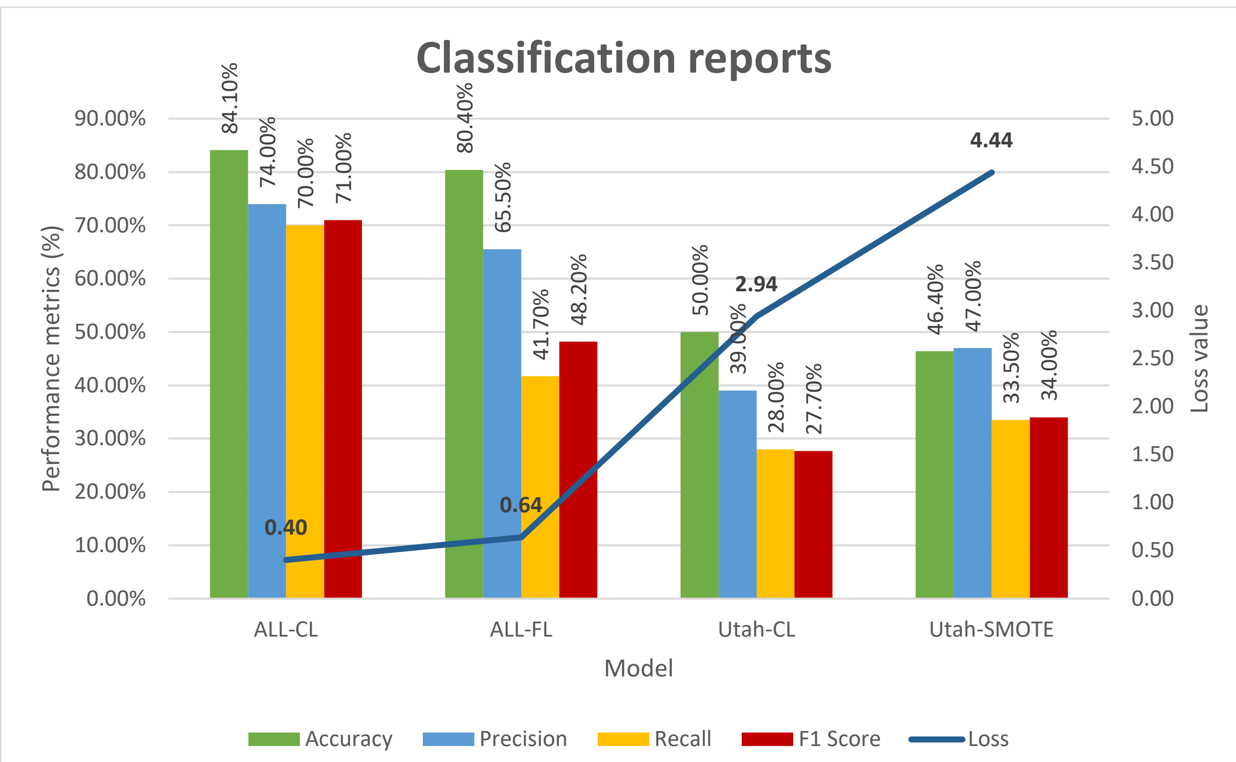

Figure 4. The comparison of classification reports for three ML models: ALL-CL (representing a centralized learning model based on all six datasets fused), FL (representing a federated learning model using six datasets), Utah-CL (a centralized learning model based on only the Utah dataset), and Utah-SMOTE (a centralized learning model based on Utah dataset augmented with synthetic data using SMOTE)

With a precision of 65.5%, the ALL-FL model outperforms both the Utah-CL and Utah-SMOTE models while coming close to the centralized benchmark, ALL-CL. Specifically, ALL-FL falls just 9.5 percentage points below ALL-CL's 74% precision but exceeds Utah-CL's 39% by a notable 26.5%. Compared with Utah-SMOTE, which achieved a precision of 47%, ALL-FL demonstrated an 18.5% improvement. Since precision measures the accuracy of positive predictions for each class, ALL-FL's strong performance highlights its reliability, being over 1.5 times more precise than the Utah-CL. Regarding recall, the ALL-FL achieved 47.1%, placing it again between ALL-CL (70%) and Utah-CL (28%). Although it does not capture as many true instances as the ALL-CL, the model still identifies a substantial portion of relevant cases, more than two-thirds of what ALL-CL detects, and clearly outperforms Utah-SMOTE, which recorded 33.5%. The F1 score, which reflects a balance between precision and recall, reached 48.2% for ALL-FL. While this lags behind ALL-CL's 71%, it is nearly double Utah-CL's performance, indicating a significant increase in overall predictive balance. Utah-SMOTE's F1 score, meanwhile, lies between those of Utah-CL and ALL-FL, further reinforcing the latter's advantage. In terms of loss, a metric indicating the deviation between predictions and actual outcomes, the ALL-FL achieved a score of 0.639. This is substantially closer to the ALL-CL's lower loss of 0.403 than to Utah-CL's much higher 2.94, demonstrating FL's strength in maintaining prediction accuracy without data centralization. Interestingly, although Utah-SMOTE outperformed Utah-CL across precision, recall, and F1, its loss was higher, suggesting significant prediction errors in certain class distributions. This disparity may indicate inconsistencies in the ability of synthetic data to represent complex class relationships.

When focusing on accuracy, a primary benchmark in most ML evaluations, the results strongly favor FL's potential. The ALL-FL model achieved nearly 96% of the accuracy recorded by the centralized ALL-CL model, despite not having direct access to the fused dataset. This highlights FL's remarkable ability to deliver near-equivalent performance while preserving data locality and privacy. For UDOT, this is particularly impactful; the ALL-FL model effectively bridges the performance gap between Utah-CL and ALL-CL. In terms of loss, FL closed more than 78% of the disparity and filled the gaps in accuracy and precision by 12% and 75%, respectively. This makes FL a practical solution for limited data and a competitive alternative to centralized learning.

Figure 5 further illustrates the advantage of the ALL-FL model by comparing the confusion matrices. In contrast to Utah-CL, which failed to identify any culverts in class 1, the ALL-FL model demonstrated outstanding performance by achieving a 97% recall for this critical class. This result even exceeded the performance of both Utah-SMOTE and ALL-CL for class 1. Although Utah-SMOTE improved the recall for class 1 to 50%, it was still far behind the recall achieved by ALL-FL. However, class 2 prediction remained a challenge for the ALL-FL model, mainly due to the absence of class 2 samples in the Ohio dataset. As a result, nearly half of the class 2 culverts were incorrectly classified as class 1, indicating a cautious yet safer misclassification pattern. In contrast, the Utah-CL model misclassified all class 2 culverts as class 4, a more problematic outcome. Interestingly, the centralized ALL-CL model also struggled with class 2, reinforcing the need for more balanced datasets across states. While Utah-SMOTE showed improvement in minority class predictions, it also introduced increased misclassification in majority classes like class 4. It suggests that although data augmentation boosts recall for underrepresented categories, it may inadvertently compromise precision in dominant ones. Still, from a practical standpoint, where correctly identifying high-risk culverts is more crucial than perfect classification of less critical ones, such trade-offs can be justified. Nonetheless, the superior balance and generalization achieved by the ALL-FL model underscore its value in settings with limited but privacy-sensitive datasets.

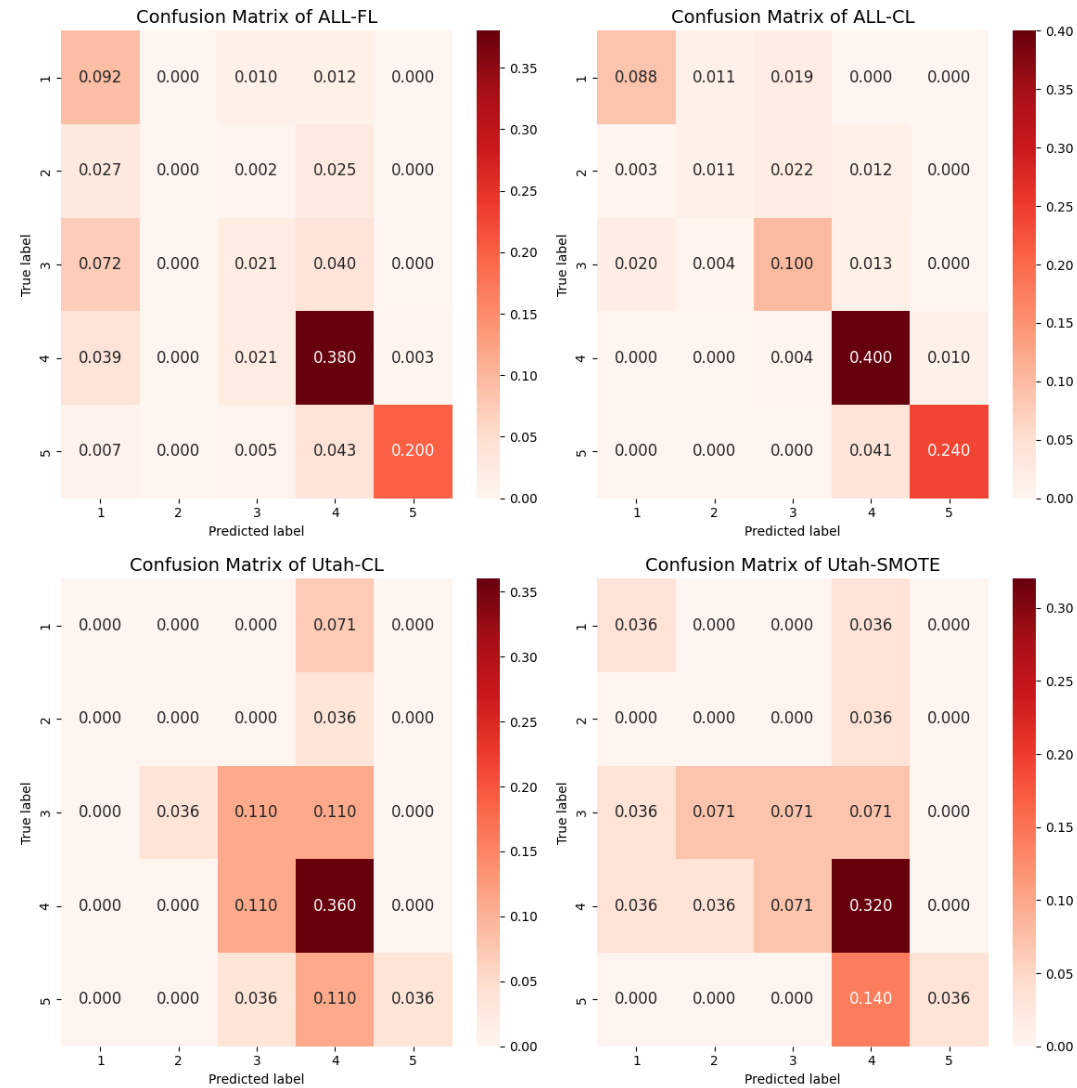

Figure 5. Confusion matrices of ALL-FL, ALL-CL, Utah-SMOTE, and Utah-CL models

This study successfully addressed its primary objectives by comprehensively developing and evaluating FL models for culvert condition prediction. First, to assess the feasibility of FL under data-limited conditions, we simulated real-world scenarios where UDOT had access only to a small local dataset while leveraging FL to train models with other DOTs' data collaboratively. The FL model effectively learned from distributed data sources without requiring direct data sharing, confirming its applicability in sparse data environments. Second, the performance of the FL models was rigorously compared with traditional centralized ML models trained on both local (Utah-CL) and fused datasets (ALL-CL), as well as with a synthetic data augmentation approach (Utah-SMOTE). The results demonstrated that FL consistently outperformed the local and augmented models and closely matched the accuracy and reliability of the centralized model trained on a fused dataset. Lastly, we quantified the privacy benefits of FL by illustrating that model training was accomplished without transmitting raw culvert data between agencies, thereby preserving compliance with data privacy standards such as GDPR and CCPA. This approach validated FL as a privacy-preserving and technically effective solution for enhancing UDOT's culvert inspection planning framework. Beyond privacy, the FL framework distributes computational demands across participating nodes, reducing the strain on centralized servers and offering a more scalable and cost-efficient solution for infrastructure asset management.

This approach facilitates the creation of more generalized and robust predictive models, even without a centralized dataset. UDOT can implement the developed FL framework as a strategic tool to enhance the efficiency and effectiveness of its culvert inspection planning process. By collaborating with other state DOTs through the FL infrastructure, UDOT can continuously improve its predictive models using external data without compromising data privacy. This allows UDOT to make data-driven decisions even with its limited internal culvert inspection records. The FL model can help prioritize inspections by identifying high-risk culverts based on predicted deterioration patterns, enabling proactive maintenance actions before failures occur. Integrating this model into existing GIS platforms or asset management systems allows for seamless visualization and scheduling of inspections across the network. Additionally, FL reduces reliance on resource-intensive traditional inspections by narrowing the focus to critical assets, optimizing budget allocation and minimizing traffic disruptions. Over time, as more agencies participate and share model updates, the collective accuracy and robustness of the system will improve, further empowering UDOT to maintain its infrastructure efficiently.

5. CONCLUSIONS AND RECOMMENDATIONS

The quality and quantity of local datasets significantly influence the effectiveness of ML models. This study presents an innovative solution to the challenges posed by limited local data when building predictive models for critical transportation infrastructure components such as culverts. Culverts often receive fewer inspections, which leads to data scarcity and avoids implementing proactive maintenance strategies, ultimately posing risks to their structural integrity and longevity. Our case study centered on UDOT, where culvert inspection data proved insufficient for developing a reliable ML model. We proposed an FL framework to address this limitation by integrating culvert data from five additional state DOTs: Colorado, New York, Vermont, Ohio, and Massachusetts.

The results underscore FL's capacity to deliver strong predictive performance for culvert condition classification while maintaining strict data privacy and compliance with data-sharing policies across jurisdictions. Unlike centralized learning, FL allows each state to retain its data and contribute only model parameters to a shared global model. Our FL-based model significantly outperformed the model trained solely on UDOT's dataset, demonstrating the advantage of this collaborative, privacy-preserving learning method. Although it did not surpass the accuracy of the centralized model trained on the fully fused dataset (ALL-CL), its performance came remarkably close, achieving 80.4% accuracy compared with ALL-CL's 84.1%, or approximately 96% of its performance.

We also experimented with SMOTE to improve class representation. The Utah-SMOTE model outperformed the basic Utah-CL model in terms of precision, recall, and F1 score, particularly in identifying underrepresented classes. However, this enhancement came at the cost of reduced overall accuracy and increased loss due to misclassification in the majority classes. While SMOTE effectively addressed class imbalance, it did not match the balanced performance achieved by the ALL-FL model, which better generalized across both frequent and rare classes while upholding privacy protections.

Our findings demonstrated the potential of FL as an innovative, privacy-preserving, and effective solution for improving culvert condition prediction in data-scarce environments. By addressing the limitations of traditional centralized ML and data augmentation methods, the FL framework enabled UDOT to build accurate predictive models without requiring access to external raw datasets. The results confirmed that FL maintains strong predictive performance and ensures compliance with data privacy regulations, making it a practical alternative for agencies constrained by data availability and sharing restrictions. Implementing this FL-based approach equips UDOT with a scalable tool for prioritizing culvert inspections more efficiently, allowing for proactive maintenance planning, reduced infrastructure risk, and optimized use of limited resources. This research provides a foundation for future collaboration among DOTs and paves the way for integrating FL into broader transportation asset management systems.

5.1 Limitations and Recommendations

- Feature Standardization Across States: The use of horizontal FL required uniform features across all datasets, leading to the exclusion of certain variables due to inconsistencies. This may have limited the model's potential. We suggest exploring alternative FL approaches, such as FTL, which can accommodate varying feature sets while supporting model generalization.
- Data Imbalance: All models, whether centralized or federated, faced challenges related to imbalanced class distributions. This led to discrepancies between accuracy, precision, and recall. Future studies could benefit from expanding dataset sizes or incorporating balancing techniques to improve robustness.
- Model Optimization: Further exploration of optimization algorithms could enhance the performance of FL models. Fine-tuning hyperparameters and adopting advanced federated optimization techniques may help narrow the performance gap with centralized models.
- Incorporating More State Inventories: Broadening the scope of participating DOTs would likely improve model generalizability and performance metrics, as more diverse data could help capture varied culvert conditions.
- Wider Applications of FL in Infrastructure: The success of FL in this study opens the door for applying this framework to other infrastructure assets, such as road pavements, bridges, or railway components, especially in cases where data sharing is constrained but predictive modeling is needed.

6. REFERENCES

Alqubaysi, Tariq, Abdullah Faiz Al Asmari, Fayez Alanazi, Ahmed Almutairi, and Ammar Armghan. 2025. "Federated Learning-Based Predictive Traffic Management Using a Contained Privacy-Preserving Scheme for Autonomous Vehicles." *Sensors (Basel, Switzerland)* 25 (4): 1116.

Anaissi, Ali, Basem Suleiman, and Widad Alyassine. 2023. "Personalised Federated Learning Framework for Damage Detection in Structural Health Monitoring." *Journal of Civil Structural Health Monitoring* 13 (2–3): 295–308. https://doi.org/10.1007/s13349-022-00615-y.

Beaver, Jesse L., and Timothy J. McGrath. 2005. "Management of Utah Highway Culverts." *Transportation Research Record*, no. 1904: 113–23. https://doi.org/10.3141/1904-12.

Beutel, Daniel J., Taner Topal, Akhil Mathur, Xinchi Qiu, Javier Fernandez-Marques, Yan Gao, Lorenzo Sani, et al. 2020. "Flower: A Friendly Federated Learning Research Framework." http://arxiv.org/abs/2007.14390.

Bukaty, Preston. 2019. *The California Consumer Privacy Act (CCPA): An Implementation Guide*. IT Governance Ltd.

Gamil, Yaser, Jonny Nilimaa, Taufik Najeh, and Andrzej Cwirzen. 2023. "Formwork Pressure Prediction in Cast-in-Place Self-Compacting Concrete Using Deep Learning." *Automation in Construction* 151: 104869.

Gao, Ce, and Hazem Elzarka. 2021. "The Use of Decision Tree Based Predictive Models for Improving the Culvert Inspection Process." *Advanced Engineering Informatics* 47: 101203.

Gillani, Maryam, and Hafiz Adnan Niaz. 2023. "Machine Learning Based Data Collection Protocol for Intelligent Transport Systems: A Real-Time Implementation on Dublin M50, Ireland." *Complex & Intelligent Systems*, 1–19.

Goto, Yumeki, Tomoya Matsumoto, Hamada Rizk, Naoto Yanai, and Hirozumi Yamaguchi. 2023. "Privacy-Preserving Taxi-Demand Prediction Using Federated Learning." In *2023 IEEE International Conference on Smart Computing (SMARTCOMP)*, 297–302. IEEE.

Hassandokht Mashhadi, Ali, Abbas Rashidi, and Nikola Marković. 2024. "A GAN-Augmented CNN Approach for Automated Roadside Safety Assessment of Rural Roadways." *Journal of Computing in Civil Engineering* 38 (2): 4023043.

Khalil, Maysaa, Moez Esseghir, and Leila Merghem-Boulahia. 2022. "A Federated Learning Approach for Thermal Comfort Management." *Advanced Engineering Informatics* 52 (February): 101526. https://doi.org/10.1016/j.aei.2022.101526.

Konečný, Jakub, H. Brendan McMahan, Felix X. Yu, Peter Richtárik, Ananda Theertha Suresh, and Dave Bacon. 2016. "Federated Learning: Strategies for Improving Communication Efficiency." *ArXiv Preprint ArXiv:1610.05492*.

Li, Jiale, Guohui Yin, Xuefei Wang, and Weixi Yan. 2022. "Automated Decision Making in Highway Pavement Preventive Maintenance Based on Deep Learning." *Automation in Construction* 135: 104111.

Li, Li, Yuxi Fan, Mike Tse, and Kuo-Yi Lin. 2020. "A Review of Applications in Federated Learning." *Computers & Industrial Engineering* 149: 106854.

Li, Tian, Anit Kumar Sahu, Ameet Talwalkar, and Virginia Smith. 2020. “Federated Learning: Challenges, Methods, and Future Directions.” *IEEE Signal Processing Magazine* 37 (3): 50–60. https://doi.org/10.1109/MSP.2020.2975749.

Li, Tian, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. 2020. “Federated Optimization in Heterogeneous Networks.” *Proceedings of Machine Learning and Systems* 2: 429–50.

Li, Xiao, Hung-lin Chi, Weisheng Lu, Fan Xue, Jianhuan Zeng, and Clyde Zhengdao Li. 2021. “Federated Transfer Learning Enabled Smart Work Packaging for Preserving Personal Image Information of Construction Worker.” *Automation in Construction* 128 (March): 103738. https://doi.org/10.1016/j.autcon.2021.103738.

Mashhadi, Ali Hassandokht, Nikola Markovic, and Abbas Rashidi. 2022. “Estimating Construction Work Zones Capacity Using Deep Neural Network.” In *Construction Research Congress 2022*, 98–107.

McMahan, Brendan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. 2017. “Communication-Efficient Learning of Deep Networks from Decentralized Data.” In *Artificial Intelligence and Statistics*, 1273–82. PMLR.

Meegoda, J. N., T. M. Juliano, L. Potts, C. Tang, and T. Marhaba. 2017. “Implementation of a Drainage Information, Analysis and Management System.” *Journal of Traffic and Transportation Engineering (English Edition)* 4 (2): 165–77. https://doi.org/10.1016/j.jtte.2017.03.002.

Mohammadi, Pouria, Sadegh Asgari, Abbas Rashidi, and Reuel Alder. 2025. “Culvert Inspection Framework Using Hybrid XGBoost and Risk-Based Prioritization: Utah Case Study.” *Journal of Construction Engineering and Management* 151 (6): 4025052.

Mohammadi, Pouria, Abbas Rashidi, and Sadegh Asgari. 2024a. “Improving Culvert Condition Prediction Models Using Federated Learning: The Case Study of Utah.” In *Construction Research Congress 2024*.

Mohammadi, Pouria, Abbas Rashidi, and Sadegh Asgari. 2024b. “Privacy-Preserving Culvert Predictive Models: A Federated Learning Approach.” *Advanced Engineering Informatics* 61: 102483.

Mohammadi, Pouria, Abbas Rashidi, and Sadegh Asgari. 2024c. “Simulating Federated Learning with Data Augmentation for Culvert Condition Prediction in Utah: A Case Study.” In *2024 Winter Simulation Conference (WSC)*, 2337–47. IEEE.

Mohammadi, Pouria, Abbas Rashidi, Masoud Malekzadeh, and Sushant Tiwari. 2023. “Evaluating Various Machine Learning Algorithms for Automated Inspection of Culverts.” *Engineering Analysis with Boundary Elements* 148: 366–75. https://doi.org/https://doi.org/10.1016/j.enganabound.2023.01.007.

Mohammadi, Pouria, Behnam Sherafat, Abbas Rashidi, and Mountain-Plains Consortium. 2023. “A Risk-Based Framework for Optimizing Inspection Planning of Utah Culverts.” Mountain-Plains Consortium.

Moretti, Nicola, Xiang Xie, Jorge Merino Garcia, Janet Chang, and Ajith Kumar Parlikad. 2021. “Developing a Federated Data Model for Built Environment Digital Twins.” In *Computing in Civil Engineering 2021*, 613–21.

(National Association of Sewer Service Companies). 2001. “NASSCO’s Pipeline Assessment and Certification Program Marriotsville,” no. Marriotsville, MD: NASSCO.

Piratla, Kalyan R., He Jin, and Sepideh Yazdekhasti. 2019. “A Failure Risk-Based Culvert Renewal Prioritization Framework.” *Infrastructures* . https://doi.org/10.3390/infrastructures4030043.

Salem, Ossama, Baris Salman, and Mohammad Najafi. 2012. “Culvert Asset Management Practices and Deterioration Modeling.” *Transportation Research Record*, no. 2285: 1–7. https://doi.org/10.3141/2285-01.

Saputra, Yuris Mulya, Dinh Thai Hoang, Diep N. Nguyen, Eryk Dutkiewicz, Markus Dominik Mueck, and Srikathyayani Srikanteswara. 2019. “Energy Demand Prediction with Federated Learning for Electric Vehicle Networks.” In *2019 IEEE Global Communications Conference (GLOBECOM)*, 1–6. IEEE.

Senapati, Sushanta, Sneha Mallik, Vipul Singh Negi, and Suchismita Chinara. 2023. “Comparison of Different Models for Federated Learning Based Parking Space Estimation.” In *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 1–6. IEEE.

Sinha, Kumares C., Samuel Labi, and Bismark R. D. K. Agbelie. 2017. “Transportation Infrastructure Asset Management in the New Millennium: Continuing Issues, and Emerging Challenges and Opportunities.” *Transportmetrica A: Transport Science* 13 (7): 591–606.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. n.d. “Web Soil Survey.” Accessed May 28, 2022. https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx.

Stoner, Michael, Weichiang Pang, and Kalyan Piratla. 2019. “Predicting Culvert Deterioration Using Physical and Environmental Time-Independent Variables.” *Journal of Pipeline Systems Engineering and Practice* 10 (4): 04019035. https://doi.org/10.1061/(asce)ps.1949-1204.0000409.

Taherkhani, Amir Hosein, Mei, Qipei, and Han Fei. 2023. “A Deep Learning Model to Predict the Lateral Capacity of Monopiles.” In *Geo-Congress 2023*, 220–27. Proceedings. https://doi.org/doi:10.1061/9780784484685.023.

Tatari, Omer, Shad M. Sargand, Teruhisa Masada, and Bashar Tarawneh. 2013. “Neural Network Approach to Condition Assessment of Highway Culverts: Case Study in Ohio.” *Journal of Infrastructure Systems* 19 (4): 409–14. https://doi.org/10.1061/(asce)is.1943-555x.0000139.

Tran, D. H., A. W. M. Ng, B. J. C. Perera, S. Burn, and P. Davis. 2006. “Application of Probabilistic Neural Networks in Modelling Structural Deterioration of Stormwater Pipes.” *Urban Water Journal* 3 (3): 175–84. https://doi.org/10.1080/15730620600961684.

Tran, H. D., B. J. C. Perera, and A. W. M. Ng. 2009. “Predicting Structural Deterioration Condition of Individual Storm-Water Pipes Using Probabilistic Neural Networks and Multiple Logistic Regression Models.” *Journal of Water Resources Planning and Management* 135 (6): 553–57. https://doi.org/10.1061/(asce)0733-9496(2009)135:6(553).

Voigt, Paul, and Axel von dem Bussche. 2017. *The Eu General Data Protection Regulation (GDPR). A Practical Guide.* 1st Ed., Cham: Springer International Publishing 10 (3152676): 10–5555.

Yang, Qiang, Yang Liu, Tianjian Chen, and Yongxin Tong. 2019. “Federated Machine Learning: Concept and Applications.” *ACM Transactions on Intelligent Systems and Technology (TIST)* 10 (2): 1–19.

Zhang, Qiqi, and Wei Pan. 2022. “Federated Learning Based Collaboration Framework of Data Sharing for Intelligent Design of Residential Buildings.” In *International Symposium on Advancement of Construction Management and Real Estate*, 516–32. Springer.

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