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**SCHOOL OF ENGINEERING**

**DEPARTMENT OF CIVIL ENGINEERING**

**BACHELOR OF EDUCATION TECHNOLOGY (CIVIL ENGINEERING)**

**TITLE: ENHANCING CONCRETE STRUCTURAL DESIGN: PREDICTIVE MODELING FOR TENSILE STRENGTH EVALUATION**

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*A Research Proposal Submitted to Dedan Kimathi University of Technology in Partial Fulfillment of the Requirements for the Award of the Degree of Bachelor of Technology in Civil Engineering.*

**2023**

# **DECLARATION**

I affirm that this project is entirely my own work, with due acknowledgment provided in the text where appropriate. To the best of my knowledge, it has not been previously submitted for the purpose of obtaining a degree or diploma at Dedan Kimathi University of Technology or any other educational institution.

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# **ABBRIVIATIONS**

OPC - Ordinary Portland Cement.

PPO - Portland Pozzolana Cement.

NNM - Neural Network Model.

# **ABSTRACT**

Precisely forecasting the tensile strength of concrete is a difficult but vital issue in the field of civil engineering, as it directly affects the longevity and structural soundness of buildings. The goal of this proposed project is to create a neural network model based on Python and PyTorch that can accurately forecast the tensile strength of concrete. Important parameters like cement type and quantity, curing time, aggregate size, and admixtures will all be taken into account by the model. Metrics like R-squared and Mean Squared Error will be used to assess the model's performance, and iterative improvements will be made to improve accuracy. This study proposal challenges the widespread belief that there is a deterministic relationship between the compressive and tensile strengths of concrete and highlights the need to evaluate them independently. The anticipated outcomes of this project could significantly impact civil engineering practices, including risk mitigation, crack prevention, and reinforcement design.

# **INTRODUCTION**

The tensile strength of concrete is a critical property in civil engineering, influencing the durability and structural integrity of constructed elements. Despite its importance, accurately predicting tensile strength remains a complex task. This project proposes the development of a Python-based neural network model with PyTorch to predict concrete tensile strength with high precision.

## **1.1 BACKGROUND OF THE STUDY**

The tensile strength of concrete is a critical property that directly affects the structural integrity and durability of buildings. However, accurately predicting this property has been a challenge in the field of civil engineering. According to a study by Bagher Shemirani and Lawaf (2023), machine learning methods have shown promise in predicting the tensile strength of concrete, indicating the potential of computational models in this area.

The American Society for Testing and Materials (ASTM) provides standard test methods for determining the tensile strength of concrete. The ASTM C496-11 outlines the standard test method for split tensile strength of cylindrical concrete samples. This standard provides a reliable method for testing the tensile strength of concrete, which will be crucial in the development and validation of the proposed model.

Furthermore, the ASTM C150-07 provides the standard specification for Portland cement, a key component in concrete. Understanding the properties of the cement used in concrete is essential as it significantly influences the tensile strength of the final product.

In his book “Understanding the Tensile Properties of Concrete,” Jaap Weerheijm (2013) discusses the importance of tensile properties in concrete and how they influence the overall performance of concrete structures. This work provides valuable insights into the factors affecting the tensile strength of concrete and will serve as a key reference in the proposed project.

This project aims to build upon these foundational works and develop a model that can accurately predict the tensile strength of concrete, thereby contributing to the field of civil engineering. The proposed model will consider key features such as the type and amount of cement, curing duration, aggregate size, and admixtures. The performance of the model will be evaluated using metrics like Mean Squared Error and R-squared, and iterative refinements will be made for enhanced accuracy.

### **HISTORY OF TENSILE STRENGTH OF CONCRETE**

The history of the tensile strength of concrete is intertwined with the history of concrete itself and the evolution of construction materials and techniques. Here’s a detailed look at this history:

**Ancient Times**

The use of concrete dates back to ancient times, with the Egyptians using early forms of concrete over 5000 years ago to build pyramids. They mixed mud and straw to form bricks and used gypsum and lime to make mortars.

**Roman Era**

The ancient Romans used a material remarkably close to modern cement to build many of their architectural marvels, such as the Colosseum, and the Pantheon. The Romans also used animal products in their cement as an early form of admixtures. However, the concept of tensile strength was not yet understood or applied.

**19th Century**

The invention of reinforced concrete in the 19th century revolutionized the construction industry. Its invention is usually attributed to Joseph Monier, a Parisian gardener who made garden pots and tubs of concrete reinforced with iron mesh; he received a patent in 1867. The reinforcing steel, which may take the form of rods, bars, or mesh, contributes tensile strength.

**20th Century**

In 1836, the first test of tensile and compressive strength took place in Germany. Tensile strength refers to concrete’s ability to resist tension, or pulling apart forces. Compressive strength refers to concrete’s ability to resist compression, or pushing together forces.

The 20th century saw the development of various types of concrete, including high-strength concrete and high-performance concrete, which have higher tensile strengths than traditional concrete. The use of admixtures became more common, allowing for the modification of concrete properties, including tensile strength.

**21st Century**

Today, the tensile strength of concrete is a critical parameter in the design and construction of structures. It is determined through laboratory tests, such as the split cylinder test, and the values obtained from these tests are used by engineers in their calculations to design structural elements effectively.

Research into improving the tensile strength of concrete continues, with studies exploring the use of different materials, such as fibers and nanoparticles, and techniques, such as curing methods and the use of admixtures. The development of machine learning and artificial intelligence has also opened up new possibilities for predicting the tensile strength of concrete, leading to more efficient and effective design processes.

## **1.2 STATEMENT OF THE PROBLEM**

The tensile strength of concrete is critical for the durability and integrity of structures. However, current methods to determine this are labor-intensive, time-consuming, and may lack precision. Additionally, it’s a misconception that high compressive strength guarantees high tensile strength. This project proposes to develop a Python-based neural network model to accurately predict concrete’s tensile strength, aiming to reduce testing time and costs, and enhance the efficiency of ensuring the quality and durability of concrete structures.

## **1.3 OBJECTIVES**

### **1.3.1 General Objectives**

Develop a Python-based neural network model using PyTorch to accurately predict concrete tensile strength in civil engineering applications.

### **1.3.2 Specific Objectives**

1. Consolidate essential parameters including cement type, curing duration, aggregate size, water content, and types of admixtures.
2. Construct and train a PyTorch neural network model specifically tailored to predict concrete tensile strength.
3. Test the model with 20% data and three lab datasets, compare outputs with lab results, and refine accuracy by adjusting nodes, layers, weights, and biases.

## **1.4 SCOPE AND LIMITATION OF STUDY**

### **1.4.1 Scope of Study**

1. **Feature Selection and Engineering:** The study will focus on identifying and selecting features crucial for predicting tensile strength, such as the amount and type of cement, water content, curing duration, aggregate size, and admixtures.
2. **Model Development:** The study will involve the design and implementation of neural network architectures using PyTorch, optimized specifically for predicting concrete tensile strength.
3. **Model Evaluation and Refinement:** The study will evaluate the model’s performance using relevant metrics (e.g., Mean Squared Error, R-squared) and refine the model by fine-tuning hyperparameters or adjusting the architecture.
4. **Data Collection:** The study will involve the collection of concrete sample data with varying amounts of cement, water, type of cement, curing duration, aggregate size, and admixtures.

### **1.4.2 Limitations of the Study**

1. **Data Availability:** The accuracy of the model is dependent on the quality and quantity of the data collected. If the data is limited or not representative of the range of concrete types used in the industry, the model’s predictions may not be accurate.
2. **Model Complexity:** While neural networks can capture complex relationships, they require significant computational resources and time for training, especially for large datasets.
3. **Generalizability:** The model is designed to predict the tensile strength of concrete based on specific features. It may not accurately predict tensile strength for concrete types not included in the training data.
4. **Assumptions:** The study assumes that the selected features are the most significant factors affecting tensile strength. However, there may be other unconsidered factors that could influence tensile strength.

## **1.5 SIGNIFICANCE AND JUSTIFICATION OF THE STUDY**

### **1.5.1 Significance of the Study**

In Kenya, the tensile strength of concrete is a critical property that significantly influences the durability and structural integrity of buildings. There have been instances where buildings have been demolished due to the formation of cracks, which could be attributed to poor tensile strength. This project, therefore, holds significant value as it aims to develop a Python-based neural network model to predict concrete tensile strength accurately. The outcomes of this project could significantly impact areas such as risk mitigation, crack prevention, and reinforcement design, potentially reducing the number of buildings at risk of demolition due to poor tensile strength.

### **1.5.2 Justification of the study**

The need for this study is justified by the current challenges in accurately predicting the tensile strength of concrete in Kenya. Existing methods are often time-consuming, labor-intensive, and may not always yield precise results. Furthermore, the assumption that high compressive strength in concrete automatically implies high tensile strength is not always accurate. This study, therefore, proposes to address these issues by developing a neural network model for accurate tensile strength prediction.

The use of machine learning, specifically neural networks, in this context is justified by their ability to capture complex relationships and patterns in data, making them well-suited for tasks such as predicting tensile strength. The proposed model, therefore, has the potential to significantly improve the accuracy and efficiency of tensile strength prediction, thereby enhancing the safety and durability of buildings in Kenya.

# **2.0 LITERATURE REVIEW**

## **2.1 INTRODUCTION**

The literature review is a fundamental component of any research project, offering a thorough exploration of the extant knowledge pertaining to the research subject. As outlined by ASTM C496-11 (2011), the literature review serves as a cornerstone for any research endeavor, particularly when it comes to understanding the split tensile strength of cylindrical concrete samples. In the context of this project, the literature review will probe into the prevailing methodologies and studies concerning the prediction of concrete tensile strength. Weerheijm (2013) emphasizes the importance of understanding the tensile properties of concrete in his book. This review will not only furnish a more profound comprehension of the current research landscape but also pinpoint the lacunae that this project aspires to bridge, a concept that Bagher Shemirani and Lawaf (2023) strongly advocate for in their research. The ensuing sections of this chapter will elaborate on the existing research, methodologies, and models germane to the prediction of concrete tensile strength, a topic extensively covered by various sources (IBM, n.d.; MIT News, 2017; PyTorch Tutorials, n.d.; Explain that Stuff, n.d.; Medium, n.d.; Coursera, n.d.; GitHub, n.d.; Springer, 2019; PLOS ONE, n.d.; Korea Science, n.d.; Springer, n.d.).

## **2.2 TENSILE STRENGTH OF CONCRETE**

Tensile strength, as defined by ASTM C496-11 (2011), is a critical property that quantifies a material’s ability to resist forces that attempt to pull it apart. For concrete, tensile strength is its capacity to withstand tensile forces or stresses. This property is of paramount importance as it directly influences the structural integrity and durability of buildings and structures.

**Significance of Tensile Strength**: Concrete is renowned for its high compressive strength, but it is relatively weak in tension. This dichotomy makes understanding its tensile strength vital in civil engineering. The importance of tensile strength manifests in several ways:

* **Crack Prevention**: Concrete structures are susceptible to cracking due to environmental factors and load-induced stresses. Tensile strength is a key factor in predicting the concrete’s resistance against cracking. By understanding and optimizing the tensile strength of concrete, engineers can design structures that are more durable and less prone to cracking. This is crucial because cracks can lead to structural failure, compromising the safety of the structure and its occupants.
* **Structural Integrity**: In structural elements like beams and slabs, tensile forces often occur due to bending. The tensile strength of concrete is crucial in resisting these forces, thereby maintaining the structural integrity of the building. A structure with adequate tensile strength can withstand external forces such as wind, seismic activity, and the weight of occupants and furniture without deforming or collapsing.
* **Reinforcement Strategies**: Concrete’s low tensile strength is compensated by using reinforcements like steel rebars, which have high tensile strength. The knowledge of concrete’s tensile strength is essential in designing these reinforcements. The placement and quantity of rebars are often determined based on the tensile strength of the concrete. This ensures that the reinforced concrete can effectively resist tensile stresses, enhancing the structure’s overall strength and durability.

**Testing and Utilization**

The tensile strength of concrete is a critical property that directly influences the structural integrity and durability of buildings and structures. It is typically determined through laboratory tests, with the split cylinder test being one of the most commonly used methods.

**Split Cylinder Test**

The split cylinder test, also known as the Brazilian test, is a popular method for determining the tensile strength of concrete. In this test, a cylindrical concrete specimen is subjected to a compressive line load along its diameter until failure occurs. The load at failure is recorded, and the tensile strength is calculated using the formula:

where:

* P is the load at failure,
* D is the diameter of the specimen, and
* L is the length of the specimen.

This test provides a relatively simple and economical way to determine the tensile strength of concrete. However, it’s important to note that the results can be influenced by several factors, including the size and shape of the specimen, the rate of load application, and the moisture condition of the specimen.

**Utilization of Test Results**

The values obtained from these tests are used by engineers in their calculations to design structural elements effectively. For instance, knowledge of the concrete’s tensile strength can help engineers determine the appropriate thickness of concrete slabs or the right amount of reinforcement needed in concrete beams. It can also guide decisions about the type of concrete mix to use for a particular application.

Moreover, understanding the tensile strength of concrete can help engineers anticipate and mitigate potential issues such as cracking. For example, if the tensile strength of the concrete is low, engineers might choose to incorporate fibers into the concrete mix to improve its tensile strength and resistance to cracking.

**Designing Structural Elements**: In structural engineering, the tensile strength of concrete, along with the strength of reinforcement bars, guides the design of critical elements like beams, columns, and slabs. Engineers consider factors such as the dimensions of the structural element, the expected loads, and the concrete’s tensile strength to calculate the necessary reinforcement. This is often done using the formula:

This approach ensures that the designed structural elements can efficiently bear the intended loads, thereby guaranteeing safety and longevity in construction. Therefore, understanding and effectively utilizing the tensile strength of concrete are fundamental in engineering for constructing durable and resilient structures. It allows engineers to design structures that not only meet their functional requirements but also adhere to safety standards and have a long service life.

## **2.3 MATERIAL SELECTION**

The process of fabricating concrete testing cylinders requires a meticulous selection of cement and chemical admixtures. The choice of these materials significantly influences the properties of the resulting concrete, including its tensile strength (Weerheijm, 2013). This literature review focuses on the different types of cement and admixtures available in Kenya, their characteristic properties, and their potential impact on the tensile strength of concrete.

### **Cement Types**

Cement, serving as the primary binder in concrete mixes, plays a crucial role in determining the properties of the resulting concrete, including its tensile strength (ASTM C150-07, 2007). In Kenya, several types of cement are commonly used, each with its unique properties:

* **Ordinary Portland Cement (OPC)**: OPC, the most commonly used type of cement worldwide, is suitable for all general types of concrete works. It is known for its versatility and compatibility with admixtures (ASTM C150-07, 2007).
* **Portland Pozzolana Cement (PPC)**: PPC is produced by grinding pozzolanic clinker with Portland cement or by blending ordinary Portland cement and fine pozzolana. It offers high resistance to chemical attacks on concrete compared with other types of cements, making it ideal for structures exposed to harsh environmental conditions (ASTM C150-07, 2007).
* **Sulphate Resisting Portland Cement**: This is a special type of PPC that contains a high proportion of fly ash and slag. It has excellent durability and strength properties, making it suitable for applications such as bridges, dams, piers, mass concrete works, and laying concrete underwater (ASTM C150-07, 2007).
* **KP Silver Rapid Hardening Cement**: This type of cement achieves high strength in the early days, making it commonly used in concrete where formworks are removed at an early stage. It allows for faster construction times and early load application (ASTM C150-07, 2007).
* **Quick setting cement**: Quick setting cement is designed to set more quickly than ordinary cement, making it a popular choice for projects that need to be completed in a short time. It is particularly useful in time-sensitive projects or in conditions where quick setting is required (ASTM C150-07, 2007).
* **Low Heat Cement**: Low Heat Cement is ideal for mass concrete works such as gravity dams as the low heat of hydration prevents the cracking of concrete due to heat. It is particularly beneficial in large structures where heat buildup can lead to thermal cracking (ASTM C150-07, 2007).

### **Admixtures**

Admixtures are chemicals added to concrete mixtures during mixing to modify certain properties, thereby increasing the quality of concrete, its usability, acceleration or deceleration of setting time, among other specific results (ASTM C496-11, 2011). Some of the most popular types of admixtures are:

* **Accelerating admixtures**: These chemicals escalate the rate of concrete strength development or shorten concrete setting time, allowing for faster removal of formwork and early application of load (ASTM C496-11, 2011).
* **Set retarding admixtures**: These chemicals delay the compound reaction that occurs when the settling process begins, making them useful in hot weather conditions where concrete may set too quickly (ASTM C496-11, 2011).
* **Water-reducing admixtures**: These chemicals help create a desired concrete slump at a lower water-cement ratio than what is normal, improving workability and reducing the risk of segregation and bleeding (ASTM C496-11, 2011).
* **Shrinkage reducing admixtures**: These chemicals produce concrete with greatly reduced drying shrinkage and potential for subsequent cracking, enhancing the durability of the structure (ASTM C496-11, 2011).
* **Air entraining admixtures**: These chemicals introduce small air bubbles into fresh concrete mixtures, improving workability and resistance to freeze-thaw cycles (ASTM C496-11, 2011).

### **Aggregates**

the selection of aggregates is another crucial factor in the creation of concrete testing cylinders. Aggregates typically constitute about 60% to 75% of the concrete volume and play a substantial role in different concrete properties such as workability, strength, dimensional stability, and durability.

In Kenya, the common types of aggregates used in concrete mixtures include:

* **Sand (Smooth Aggregate)**: Sand is a fine aggregate, used in the creation of concrete mixes. The quality of sand significantly affects the performance of concrete. Sand with round grains enhances the workability of concrete, while sand with angular and flaky grains can negatively affect workability.
* **Ballast/Kokoto (Coarse Aggregate)**: Ballast, or Kokoto as its commonly known in Kenya, is a coarse aggregate that is used in concrete. It is usually made of crushed stone. The size of the aggregate can significantly affect the strength of the concrete. Larger aggregates tend to reduce the workability of the concrete but are often more economical.
* **Gravel**: Gravel is another type of coarse aggregate used in concrete. It is often used in concrete mixes for roads and large structures due to its strength and durability.

The choice of aggregate depends on its intended use, the desired concrete properties, and local availability. For instance, if high strength is required, a higher proportion of coarse aggregates can be used. On the other hand, if workability is a priority, a higher proportion of fine aggregates may be beneficial.

The selection of materials for the creation of concrete testing cylinders involves a careful consideration of the types of cement, admixtures, and aggregates available, as well as their characteristic properties. The optimal combination of these materials can significantly affect the tensile strength of the resulting concrete.

## **2.4 NEURAL NETWORKS**

Neural networks are a type of machine learning that emulate the human brain and solve common problems in AI. They consist of node layers, each with an input, output, weight, and threshold. They use training data to learn and improve their accuracy over time. They can be feedforward or backpropagation.

Neural networks were first proposed in 1944 by Warren McCullough and Walter Pitts, two University of Chicago researchers who moved to MIT in 1952 as founding members of what’s sometimes called the first cognitive science department. Neural nets were a major area of research in both neuroscience and computer science until 1969. The technique then enjoyed a resurgence in the 1980s, fell into eclipse again in the first decade of the new century, and has returned like gangbusters in the second, fueled largely by the increased processing power of graphics chips.

**Neural Networks in PyTorch**

PyTorch is a popular framework for building neural networks. Neural networks in PyTorch are constructed using the torch.nn package. Every module in PyTorch subclasses the nn.Module. A neural network is a module itself that consists of other modules (layers). This nested structure allows for building and managing complex architectures easily.

In PyTorch, you define your neural network by subclassing nn.Module, and initialize the neural network layers in \_\_init\_\_. Every nn.Module subclass implements the operations on input data in the forward method.

To use the model, you pass it the input data. This executes the model’s forward, along with some background operations. Do not call model.forward() directly! Calling the model on the input returns a 2-dimensional tensor with dim=0 corresponding to each output of 10 raw predicted values for each class, and dim=1 corresponding to the individual values of each output. We get the prediction probabilities by passing it through an instance of the nn.Softmax module.

**Application to Our Project**

In the context of our project, a neural network can be trained to predict the tensile strength of concrete. The network would take as input the features of the concrete (such as the amount and type of cement, water content, curing duration, aggregate size, and admixtures), and output the predicted tensile strength.

Machine learning methods have been utilized to simulate and forecast the compressive strength of concrete. Various deep neural networks were simulated using different optimizers to change the number of neurons present in every hidden layer. The models take 4 features as input and the result will be predicted by the trained artificial neural network models (ANN) models. These models take the content of water, cement, sand, and gravel.

The comparisons that have been done between the predictions of the models and experimental results have shown that the models make predictions about the compressive strength of concrete with an accuracy level of approximately 80 percent.

## **2.5 CASE STUDY**

1. **Prediction of high-performance concrete compressive strength using deep learning techniques**: This study was conducted by Naimul Islam, Abul Kashem, Pobithra Das, Md. Nimar Ali & Sourov Paul. They proposed four deep learning approaches: BiLSTM, CNN, GRU, and LSTM models, which is rarely seen in the literature. The model was developed using a large database, including details about cement, fly ash, coarse aggregate, sand, water, age, and blast furnace slag as input variables and compressive strength as an output variable. This approach allowed them to create a comprehensive model that could accurately predict the compressive strength of high-performance concrete, providing valuable insights for the construction industry.
2. **Modeling of strength of high-performance concrete using artificial neural networks**: This study was conducted by I.-C. Yeh. The study demonstrated the possibilities of adapting artificial neural networks (ANN) to predict the compressive strength of high-performance concrete. Yeh’s work highlighted the potential of ANNs as a powerful tool for modeling complex relationships in construction materials, paving the way for more sophisticated prediction models in the future.
3. **Prediction of tensile strength of concrete using machine learning methods**: In a study conducted by Bagher Shemirani and Lawaf (2023), machine learning methods were utilized to simulate and forecast the tensile strength of concrete. Various deep neural networks were simulated using different optimizers to change the number of neurons present in every hidden layer. The models took 4 features as input and the result was predicted by the trained artificial neural network models (ANN) models. These models took the content of water, cement, sand, and gravel. The models made predictions about the tensile strength of concrete with an accuracy level of approximately 80 percent, demonstrating the effectiveness of machine learning methods in predicting concrete properties.
4. **Prediction of compressive strength of concrete using artificial neural networks**: This study was conducted by Palika Chopra, Rajendra Kumar Sharma, and Maneek Kumar. They compared concrete strength prediction techniques with the artificial neural network approach. Their work provided valuable insights into the advantages and limitations of different prediction techniques, contributing to the ongoing development of more accurate and reliable prediction models.
5. **Using Neural Networks to Prediction of compressive strength of heavy concrete**: This study was conducted by Larisa Naykhanova, Solbon Lkhasaranov, Oksana Khokhlova, Lyubov Goryunova, Inga Evdokimova, and Vladislav Goryunov. They used neural networks to predict the compressive strength of heavy concrete. Their research highlighted the potential of neural networks in predicting the properties of specialized types of concrete, such as heavy concrete, expanding the scope of machine learning applications in the construction industry.

## **2.6 LITRATURE REVIEW SUMMARY AND RESEARCH**

### **2.6.1 Summary**

The literature review explored various studies and methodologies related to the prediction of concrete tensile strength. It highlighted the use of machine learning methods, particularly neural networks, in predicting compressive strength and the factors influencing this property. The review also discussed the testing tensile strength in the lab. Several case studies were examined, demonstrating the effectiveness of machine learning methods in predicting the compressive strength of concrete. These studies provided valuable insights into the use of neural networks and machine learning methods for predicting the tensile strength of concrete.

### **2.6.2 Research Gap**

Despite the significant advancements in predicting the tensile strength of concrete, there are indeed several areas that warrant further exploration:

1. **Currently Gaining grounds in Kenya**: While machine learning has been widely applied in predicting concrete tensile strength, there is a noticeable lack of research focusing specifically on the Kenyan context. This project aims to address this gap by developing a model that is tailored to the unique conditions and requirements of Kenya, taking into account local construction practices, materials, and environmental factors.
2. **Need for More Accurate Predictions**: Existing studies have achieved a certain level of accuracy in predicting tensile strength, but there is always room for improvement. This project aims to enhance the accuracy of predictions by optimizing the neural network model, exploring different architectures, training algorithms, and hyperparameters to achieve the best possible performance.
3. **Need for Real-World Validation**: While theoretical models and simulations are valuable, there is a need for more studies that validate the predictions of the model that we will build with real-world data. This project aims to address this gap by testing the model with actual data from concrete samples, providing a rigorous validation of the model’s performance and ensuring its applicability to real-world scenarios.

By addressing these gaps, this project aims to make a significant contribution to the field of civil engineering, enhancing the safety and durability of buildings in Kenya. The insights gained could also be valuable for other regions with similar conditions, potentially benefiting the global construction industry.

# **3.0 METHODOLOGY**

## **3.1 OVERVIEW**

The methodology section of this proposal will outline the step-by-step approach we will take to achieve the objectives of the project. It will provide a detailed explanation of how we will collect and prepare the necessary data, develop and train the Tensile strength Prediction model, saving the model for use.

Figure 1 Flowchart for the project.

## **3.2 DATA COLLECTION**

The data collection process for this project involves several key steps:

1. **Sample Preparation:** Prepare concrete samples with varying amounts and types of cement, water content, curing duration, aggregate size, and admixtures. For this project, you will be molding concrete cylinder with diameter-to-height ratio of 2:1.
2. Selection of Materials: The first step in our methodology involves the selection of materials. We consider three types of cement (Ordinary Portland Cement, KP Silver Rapid Hardening Cement and Quick Setting Cement), and three types of admixtures (Air Entraining, SikaRapid(liquid hardening accelerator), ). We also consider three different aggregate sizes (5mm, 10mm, and 20mm).
3. Preparation of Mixes: For any combination of cement type, admixture, and aggregate size, we prepare a concrete mix. The cement-water ratio varies from 0.45 to 0.60.

| **Cement Type** | **Admixture** | **Cement-Water Ratio** | **Aggregate Size** |
| --- | --- | --- | --- |
| OPC | Air-Entraining | 0.45 | 5mm |
| KP Silver | Rapid Hardening | 0.50 | 10mm |
| Quick Setting | Accelerating | 0.60 | 20mm |

**NB:** To find the total amount of combinations / Number of samples to collect, multiply the number of options for each factor:

3 (Cement Type) x 3 (Admixture) x 3 (Cement-Water Ratio) x 3 (Aggregate Size) = 81

Consequently, this configuration entails a potential 81 combinations for testing the tensile strength of concrete cylinders. Correspondingly, this necessitates a dataset comprising 81 rows or samples to encapsulate the entirety of these combinations.

1. **Curing:** After an initial 24-hour setting period, the molded cylinders are demolded and submerged in water for curing until the specified testing age of 7 days. This immersion allows the concrete to continue its hydration process, enhancing strength development and minimizing cracking risks. Curing plays a pivotal role by facilitating optimal chemical reactions within the concrete mix, ensuring its complete hardening and durability for accurate testing and long-term performance assessment.
2. **Tensile Strength Testing:** Perform the split cylinder test on each sample to measure its tensile strength. This involves applying a gradually increasing load to the sample until failure occurs. The tensile strength is then calculated using the formula:

1. **Data Recording:** Record the features of each sample (such as the amount and type of cement, water content, curing duration, aggregate size, and admixtures) and its measured tensile strength. This data will be used to train and evaluate the neural network model.
2. **Data Organization:** Organize the collected data in a structured format, such as a spreadsheet. Each row represents a sample, and each column represent a feature or the tensile strength.

### **3.2.1 DATA PREPROCESSING.**

The collected data will be preprocessed to prepare it for the neural network model. This may involve normalizing the data, handling missing values, and converting categorical variables into a format that can be used by the model.

An essential step in constructing the Predictive Model involves the strategic division of the dataset, known as data partitioning. This process entails segregating the available dataset into two distinct subsets:

1. **Training Set:** This pivotal subset, typically constituting around 80% of the dataset, forms the basis for training the predictive model. It facilitates the model in comprehensively understanding intricate patterns, relationships, and underlying structures inherent in the data.
2. **Testing Set:** Constituting the remaining 20% of the dataset, the testing set remains entirely separate from the training set. Its primary purpose lies in objectively assessing the model's performance. This set validates the model's ability to generalize and make accurate predictions on unseen data, ensuring robustness and reliability.

To maintain an unbiased evaluation and avoid any inherent bias, the data partitioning adheres strictly to random selection criteria. This randomization process eliminates potential structural influences within the dataset, guaranteeing that both the training and testing sets equally represent the dataset's characteristics. This meticulous approach fosters a more comprehensive evaluation, enhancing the model's performance assessment and overall effectiveness.

In our project, we will be working with a CSV dataset that contains numerical data about various aspects of concrete. However, we might find that the data we have collected may not be sufficient to build a robust and accurate model. In such cases, we have several strategies at our disposal to enhance both the quality and quantity of our data:

1. **Data Augmentation**: While this technique is more commonly used with image data, for numerical data like ours, we can create new data points by adding small variations to our existing data. This not only increases the volume of our data but also helps our model become more robust to such variations, thereby improving its generalization ability.
2. **Collect More Data**: If feasible, we can gather more data from our data source. This could involve conducting more experiments with different proportions of cement, water, and aggregate sizes, or using different types of cement and admixtures.
3. **Data Generation**: We can employ synthetic data generation methods to create more data. However, we should use synthetic data cautiously, as it may not fully encapsulate the complexities of real-world data. For instance, we could use a method like bootstrapping, which involves resampling our existing data with replacement.
4. **Use of External Datasets**: We can incorporate external datasets that are similar or related to our data. For example, we could look for datasets from other studies on concrete strength. It’s crucial to ensure that the external data is compatible with our data, meaning it should be from a similar distribution and should not contradict our existing data.
5. **Interpolation or Extrapolation**: For our numerical data, we might be able to use interpolation or extrapolation to estimate data between or beyond our actual data points. Interpolation can help us estimate values within the range of our data, while extrapolation can help us predict values outside the range of our data.

By implementing these strategies, we aim to improve the robustness of our model and ensure its performance is reliable and accurate. It’s important to remember that the quality of our data is often more important than the quantity. Therefore, while we strive to increase our data volume, we must also focus on maintaining and enhancing data quality. This will ensure that our model’s predictions on the tensile strength of concrete are as accurate as possible.

## **3.3 FEATURE SELECTION**

In the quest to predict concrete tensile strength accurately, it's crucial to identify and refine specific factors that wield significant influence. These pivotal parameters encompass various elements:

1. **Cement and Water Proportions:** The quantities of cement and water utilized profoundly affect the concrete's final strength. Adjusting these proportions can directly impact the resulting tensile strength.
2. **Type of Cement (e.g., OPC, PPC):** Different cement types possess distinct characteristics that distinctly influence how concrete behaves under tension. Recognizing these variations aids in predicting tensile behavior accurately.
3. **Curing Duration:** The duration and conditions of the curing process significantly impact concrete strength development. Variations in curing duration can notably affect the concrete's tensile properties.
4. **Aggregate Size:** The size and distribution of aggregates incorporated into the concrete mix play a critical role in determining overall strength. Altering aggregate sizes can have tangible effects on tensile behavior.
5. **Admixtures' Impact:** The inclusion of admixtures, such as accelerators or plasticizers, can modify concrete properties. Understanding their influence helps in precise predictions of tensile strength.

Engineering these features involves not just identifying them but refining their representation for optimal integration into predictive models. Techniques involving normalization, scaling, or feature manipulation are applied to ensure compatibility and empower models to comprehensively grasp and utilize these features. These methods enhance the model's capacity to interpret intricate relationships between parameters, ultimately refining the accuracy and dependability of concrete tensile strength predictions.

## **3.4 MODEL DEVELOPMENT (TENSILE PREDICTOR)**

The proposal aims to develop a robust neural network model using PyTorch, intending to process concrete features as input and generate precise predictions for tensile strength as the output. The architecture design involves tailoring the number of layers, neurons within each layer, and selecting suitable activation functions to optimize prediction accuracy.

We can’t give a definitive answer on how many neural network layers we should use, as it’s dependent on various factors. These include the complexity of the problem, the amount and quality of the data, the computational resources available, and the desired accuracy and performance of the model. However, we can provide some general guidelines and methods to help us choose a reasonable number of layers for our model.

One method we recommend is a trial-and-error approach. Start with a simple model with one or two hidden layers and a few neurons each. Gradually increase or decrease the number of layers and neurons until we find a good balance between complexity and simplicity. We suggest using cross-validation techniques such as k-fold cross-validation or leave-one-out cross-validation to evaluate our model on different subsets of our data. Selecting the best model based on metrics such as mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), or R-squared (R2). Techniques such as grid search or random search can be used to systematically explore different combinations of layer sizes and neuron numbers within a predefined range.

Another method is to use some rules of thumb or heuristics that are based on empirical observations or theoretical principles. For instance, some sources suggest that adding more hidden layers will improve the performance of our model until it starts to overfit our data. Overfitting means that the model learns too much from the training data and fails to generalize well to new data. In this case, we might want to add regularization techniques such as dropout, weight decay, batch normalization, or early stopping to prevent overfitting. Some sources also suggest that adding more neurons per layer will increase the capacity of our model until it reaches a point where adding more neurons does not improve its performance significantly. In this case, we might want to reduce the number of neurons per layer by using techniques such as pruning or quantization.

The goal is to craft a neural network capable of comprehensively understanding complex relationships between concrete characteristics and their impact on tensile strength, ensuring highly reliable predictions.

## **3.5 LOSS FUNCTION AND MODEL OPTIMIZATION**

### **Loss Function**

A loss function measures the difference between the model’s predictions and the actual values. The choice of the loss function can significantly affect the model’s performance. For regression tasks, such as predicting the tensile strength of concrete, common loss functions include Mean Squared Error (MSE) and Mean Absolute Error (MAE). MSE is more sensitive to outliers than MAE, as it squares the differences before averaging them. Therefore, the choice between MSE and MAE depends on whether large errors are particularly undesirable in the problem at hand.

### **Model Optimization**

Model optimization is the process of adjusting the model’s parameters to improve its performance. The most common method for model optimization is gradient descent, which iteratively adjusts the model’s parameters in the direction that reduces the model’s error. The learning rate, which determines the size of the steps in the gradient descent, is a crucial parameter that can significantly affect the model’s performance. A learning rate that is too high can cause the model to overshoot the optimal solution, while a learning rate that is too low can cause the model to converge slowly or get stuck in a suboptimal solution.

## **3.6 TRAINING PROCESS**

The training process encompasses feeding a portion, typically 80% of the original dataset, to the model for learning. This phase involves continuous iterations, where the model makes predictions and adjusts its parameters to minimize the disparity between these predictions and the actual values. In instances where the dataset is substantial, an additional subset, known as the validation set, might also be utilized. This set, distinct from both the training and testing sets, aids in gauging the model's generalization capability. Monitoring the model's performance on this validation set alongside the training data is essential. It ensures the model is not overly fixating or 'overfitting' to the intricacies of the training data but instead learns to generalize well to unseen data, ultimately enhancing its predictive ability.

## **3.7 EVALUATION PROCESS**

**Model Testing**: Post-training, the model will be tested on the 20% data set aside for this purpose. This will provide an initial measure of the model’s performance on unseen data. The model’s performance will be evaluated using accuracy as the metric.

**Model Evaluation**: To further evaluate the model’s predictive capabilities, three additional sets of concrete sample data will be collected from the laboratory. The model will use the features from this new data to make predictions. By comparing these predictions to the actual tensile strengths measured in the laboratory, we can assess the model’s ability to generalize to new, unseen data.

## **3.8 MODEL REFINEMENT AND SAVING**

### **Model Refinement**

After the initial evaluation, the model may need to be refined to improve its accuracy. This could involve adjusting the architecture of the model, such as adding or removing layers, changing the number of neurons in each layer, or changing the activation function. It could also involve tuning the model’s parameters, such as the learning rate or the regularization parameter. The refinement process is iterative, meaning that after each refinement, the model is retrained and reevaluated, and further refinements are made based on the results.

### **Saving the Model**

Once the model has been trained and refined, it will be saved for future use. This involves saving the model’s parameters, which have been learned during training, as well as the model’s architecture. The saved model can then be loaded at a later time to make predictions on new data. Saving the model does not just involve saving the final trained model. It’s also important to save the best model during training, as the final model may not be the best one due to overfitting.

## **3.9 DOCUMENTATION AND REPORTING**

Throughout the project, all processes, methodologies, results, and insights will be thoroughly documented. This includes documenting the data collection and preprocessing methods, the model development and training process, the model evaluation and refinement steps, and the final results. The documentation will provide a detailed account of the project, allowing others to understand the work that has been done, reproduce the results, or build upon the project in the future.

In addition to the documentation, a comprehensive report summarizing the methodologies, results, and implications for civil engineering practices will be prepared. The report will present the key findings of the project in a clear and concise manner, making it accessible to both technical and non-technical audiences.

## **3.10 BUDGET**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | CEMENT | QUANTITY | PRICE | ADMIXTURE | QUANTITY | PRICE |
| 1 | OPC | 1 | 900 | Accelerator | 1 | 700 |
| 2 | KP Silver | 1 | 900 | Shrinkage-Reducer | 1 | 750 |
| 3 | Quick Setting | 1 | 800 | Air-Entraining | 1 | 800 |
| TOTAL |  | 3 | 5500 |  | 3 | 4500 |
|  |  |  |  |  |  |  |
| GRAND TOTAL | 10000 |  |  |  |  |  |

## **3.11 WORK PLAN**

|  |  |  |  |
| --- | --- | --- | --- |
|  | OCTOBER | NOVEMBER | DECEMBER |
| Selection of the project |  |  |  |
| Introduction |  |  |  |
| Literature review |  |  |  |
| Methodology and expected results |  |  |  |
| Project proposal presentation |  |  |  |

# **4.0 EXPECTED RESULTS AND OUTCOMES**

The primary objective of this project is to create a predictive model for the tensile strength of concrete based on various factors such as the type of cement, type of admixture, cement-water ratio, and aggregate size. The expected results and outcomes of this project are as follows:

1. **Comprehensive Dataset**: The project will result in a comprehensive dataset of 81 different combinations of concrete mixes, each represented by a cylinder with a diameter-to-height ratio of 2:1 and a height of 150mm. This dataset will encapsulate the entirety of these combinations and serve as a valuable resource for future research and development efforts in the field of concrete technology.
2. **Predictive Model**: The project will develop a predictive model that can accurately estimate the tensile strength of concrete based on the selected factors. This model will be validated using a separate set of data and its performance will be evaluated based on its accuracy in predicting the tensile strength of concrete.
3. **Insights into Material Properties**: Through the testing and analysis of different concrete mixes, the project will provide valuable insights into the properties of different types of cement, admixtures, and aggregates, and their impact on the tensile strength of concrete. These insights could lead to the development of new concrete mixes with improved properties.
4. **Contribution to the Field of Concrete Technology**: By advancing our understanding of the factors that influence the tensile strength of concrete, this project will make a significant contribution to the field of concrete technology. The findings of this project could inform the design of more durable, sustainable, and cost-effective concrete structures in the future.

# **APPENDICES**

**DATA COLLECTION PROCEDURE**

**EQUIPMENTS**

To perform the split cylinder test, you will need the following equipment and materials:

* A compression testing machine that can apply a diametral compressive load along the length of the specimen at a continuous rate.
* A capping fixture to hold and secure the specimen in place on the testing machine.
* A combination and centering square to ensure that the specimen is aligned properly on the testing machine.
* Pi tape to measure and mark the diameter and height of each specimen.
* Calipers to measure and record the dimensions of each specimen.
* A ruler to measure and record the length of each specimen.
* A camera to capture images of each specimen before and after testing.

**PROCEDURE**

The steps for performing the split cylinder test are as follows:

1. Verify that your compression testing machine is in working order and calibrated according to standards.
2. Prepare your concrete samples for testing. You will need at least enough specimens with different cement types, admixtures, cement-water ratios, and aggregate sizes. You can use a standard size of 150 mm diameter and 300 mm height for your specimens, or you can use other sizes as long as they have a consistent ratio of diameter-to-height (2:1).
3. Use a capping fixture to hold and secure your specimens in place on your compression testing machine. Make sure that there is no gap between your specimens and that they are aligned properly on both sides of the testing machine.
4. Use a combination and centering square to ensure that your specimens are aligned properly on both sides of your compression testing machine. Make sure that there is no deviation from the center line or from one side edge of another specimen. You can refer to [this document] for more details on how to use your combination and centering square.
5. Use pi tape, calipers, ruler, camera, etc., as necessary, to measure and record various dimensions of each specimen before testing them under compression load. These dimensions include:
   * Diameter (d) at one end
   * Height (h) at one end
   * Length (l) along one side
   * Cross-sectional area (A) at one end
6. Place each specimen between two loading surfaces on your compression testing machine according to their dimensions recorded in step 6. Make sure that there is no gap between any two loading surfaces or between any loading surface and any edge or corner of another specimen or loading surface.
7. Start applying a diametral compressive load along both sides of each specimen at a continuous rate until failure occurs along their vertical plane (the generatrix). You can refer to [this document] for more details on how much load you should apply per second depending on whether you are using an open-loop or closed-loop machine.
8. Stop applying load when failure occurs along either side or when you reach a predetermined number of cycles (usually 10). Record this value as Nc (number of cycles).
9. Calculate the tensile strength (σt) by dividing Nc by dA/2l, where dA/2l is half of the cross-sectional area at one end divided by half of the length along one side.
10. Repeat steps 7 through 10 for all specimens with different cement types, admixtures, cement-water ratios, and aggregate sizes.

**DATA RECORDING**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Samples | Cement amount  (g)  (integer) | Water  (g)  (integer) | Type of cement  (string) | Average Aggregate size  (integer) | Aggregate  (Coarse)  Amount  (g) | Aggregate  (SAND)  Amount  (g) | Curing Duration  (days)  (integer) | Admixtures  (string) | Load at Fracture  (max Load)  (N)  (integer) | Tensile strength |
| 1 |  |  |  |  |  |  |  |  |  |  |
| 2 |  |  |  |  |  |  |  |  |  |  |
| 3 |  |  |  |  |  |  |  |  |  |  |
| 4 |  |  |  |  |  |  |  |  |  |  |
| 5 |  |  |  |  |  |  |  |  |  |  |

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