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Influence of Sodium Silicate on the Properties of Wood Ash Blended Cement Concrete

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Authors contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

This study explores the impact of sodium silicate on wood ash blended cement concrete, which contributes significantly to CO_2 emissions. This research holds great potential for the construction industry by aiding in the reduction of greenhouse gas emissions, conserving natural resources, and promoting waste minimization. The specific research objectives are Characterizing sand, granite, and wood ash, Producing concrete mixes with wood ash and sodium silicate (Na_2SiO_3) replacements of 0.5%, 1.0%, 1.5%, and 2.0%, and determine their compressive strength, workability, density, and water absorption, and Developing a Long Short Term Memory (LSTM) deep learning model to determine optimal proportions of cement, w/c ratio, wood ash, and sodium silicate to achieve target compressive strength, workability, water absorption, and density in

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concrete mixes. Concrete specimens were tested for compressive strength, workability, density, and water absorption. A Long Short Term Memory (LSTM) machine learning model is significant because it is designed to capture historical information of time series data and is suitable for predicting long-term nonlinear series. The LSTM predicted compressive strength based on inputs of cement, water/cement ratio, sodium silicate, and wood ash. Results indicated that sodium silicate significantly enhanced early compressive strength and workability, making this blend a viable option for sustainable construction where early strength is essential.

Keywords: Wood ash; blended cement concrete; sodium silicate; long short-term model (LSTM).

1. INTRODUCTION

Concrete, as a cornerstone of modern construction, is lauded for its unparalleled strength, durability, and versatility. It is the most widely used material in the construction industry after water due to its excellent mechanical properties and low cost (Monteiro et al., 2017). With an annual consumption of approximately 10 billion tonnes (Yaprak et al., 2011), ordinary Portland cement is a primary ingredient in concrete production. However, the production of cement significantly contributes to CO_2 emissions, raising environmental concerns. The cement industry accounts for approximately 7% of all greenhouse gas emissions, releasing about 222 kg of CO_2 per tonne of cement produced. The energy-intensive processes involved in cement production further exacerbate this issue, with predictions indicating a potential 50% rise in CO_2 emissions by 2020.

In response to these challenges, there have been ongoing efforts to reduce the environmental impact of cement production through the use of supplementary cementitious materials (SCMs). These include industrial and agricultural by-products such as fly ash, slag, and more recently, wood ash. The incorporation of wood ash, a by-product of biomass combustion, presents a promising eco-friendly alternative due to its pozzolanic properties, which can enhance concrete performance (Teker Ercan et al., 2023). Additionally, the use of chemical admixtures like sodium silicate (Na_2SiO_3) can further modify the properties of wood ash blended cement concrete, potentially improving workability and strength. Sodium silicate reacts with calcium hydroxide to form calcium silicate hydrate (C-S-H), crucial for concrete strength.

Concrete's pivotal role in construction necessitates continuous improvement to meet the growing demands for sustainable and high-performance materials. Research indicates that using wood ash as a partial cement replacement can reduce compressive strength due to its filler-like behavior. However, sodium silicate may enhance compressive strength, tensile strength, and resistance to environmental factors while improving flowability and reducing segregation. This research aims to evaluate sodium silicate's potential in enhancing the properties of wood ash blended cement concrete, providing practical solutions for reducing environmental impact while maintaining performance.

This study seeks to contribute to the development of environmentally sustainable construction materials that do not compromise performance. By exploring the incorporation of wood ash and sodium silicate into concrete production, the research aims to address waste disposal issues and reduce the carbon footprint associated with cement manufacturing. The scope encompasses detailed material characterization, performance comparison between wood ash blended cement concrete and traditional ordinary Portland cement concrete, and the development of predictive models to assess the impacts of these materials on concrete properties. The overall aim of this project is to investigate the influence of sodium silicate (Na_2SiO_3) on the workability and strength of wood ash blended cement concrete and develop a predictive model using deep learning. The specific objectives are to:

i. Characterize sand, granite, and wood ash.
ii. Produce concrete mixes with wood ash and sodium silicate (Na_2SiO_3) replacements of 0.5%, 1.0%, 1.5%, and 2.0%, and determine their compressive strength, workability, density, and water absorption.
iii. Develop a Long Short Term Memory (LSTM) deep learning model to determine optimal proportions of cement, w/c ratio, wood ash, and sodium silicate to achieve target compressive strength, workability, water absorption, and density in concrete mixes.

2. LITERATURE REVIEW

Concrete, renowned for its affordability, widespread availability, durability, and resilience in diverse climatic conditions, stands as one of the oldest and most utilized construction materials globally. Its production surpasses that of steel by tenfold in terms of tonnage. In contrast, materials like steel and polymers, although possessing their unique advantages, tend to be costlier and less ubiquitous than concrete. Despite its high compressive strength, concrete is inherently brittle and exhibits lower tensile strength, necessitating reinforcement to withstand tensile stresses (Tantawi et al., 2015). Typically, steel is employed for this purpose. Concrete is a heterogeneous mixture that consists of the following components: Aggregates, Cement, Water and Additives.

The basic properties of concrete are defined as follows. Workability is the ability of freshly mixed concrete to be easily mixed, placed, compacted, and finished without segregation or loss of uniformity. Workability of concrete can be carried out using the following test include; slump, flow test, vebe test and compacting factor test. Compressive strength is one of the most common methods to evaluate concrete performance by measuring the compressive strength of hardened concrete at an age of 28, 56, 120 days. This test can be done by breaking a concrete specimen in a compression testing machine. The specimens can be a standard cube specimen of 150 ×150 × 150 mm^3 or a standard cylindrical concrete specimen of 150 mm × 300 mm. Strength of the cylinder is roughly 80% of the strength of the cube. There are other tests that can be used to find the compressive strength of in-place concrete such as the hammer test and the coring test. In practice, compressive test is carried out at the age of 3, 7, 14 and 28 days. The long-time span needed for the 28-day test, makes it more advantageous to use other tests that predict the strength of hardened concrete. Concrete density refers to the mass per unit volume of freshly mixed concrete. It is typically measured in kilograms per cubic metre (kg/m^3) or pounds per cubic foot (lb/ft^3). The density of concrete can vary depending on the mix proportions and the density of its components (cement, aggregates, water, and admixtures). Water absorption of concrete refers to the ability of concrete to absorb water when immersed or exposed to moisture. This property is crucial because it affects the durability and performance of concrete structures, especially in environments where moisture exposure is common, such as bridges, dams, and buildings. High water absorption can lead to freeze-thaw damage, chemical attack, and corrosion of embedded steel. Low water absorption indicates better resistance to environmental conditions, maintaining structural integrity over time. Water absorption of concrete is a critical property affecting its durability and longevity in service.

Pozzolans: Pozzolans are the most commonly used mineral admixtures in modern concrete production. A pozzolan is defined as a material that contains siliceous or both siliceous and aluminous components. While these substances have little or no cementitious value on their own, they chemically react with calcium hydroxide in the presence of water at ambient temperatures to form cement-like compounds. The pozzolanic reaction involves the interaction between the silica and alumina components of the pozzolan, water, and calcium hydroxide. In concrete production, specific pozzolans are added as partial replacements for OPC to achieve desired properties (Xiao et al., 2019). Although the early strength of pozzolan-blended cement may be lower, finer pozzolans can mitigate this effect by filling spaces between cement particles, resulting in denser concrete. The improved durability also extends the service life of structures, reducing maintenance and replacement costs (Mishra, 2019). The primary pozzolanic reaction is represented as:

$$3Ca(OH)_2 + SiO_2 \rightarrow 3CaO.SiO_2 + 3H_2O$$

The term pozzolan refers to various materials with diverse properties and origins, including organic and synthetic sources. Industrial waste, such as fly ash and silica fume, as well as thermally activated clays like metakaolin, exhibit pozzolanic activity. Today, materials such as metakaolin, fly ash, and rice husk ash are widely used as supplementary cementitious materials, contributing to sustainable concrete production.

Pozzolans are classified into two categories: natural and artificial. Natural pozzolans include materials like calcined diatomaceous earth, volcanic ash, and shales. On the other hand, artificial pozzolans comprise substances such as silica fume, wood ash, fly ash, and blast furnace slag. The focus of this research is on wood ash. Incorporating pozzolans into concrete improves resistance to environmental degradation by reducing permeability, absorption, and ion diffusion. Despite their impact on permeability, pozzolans do not negatively affect carbonation depth if the concrete's strength remains consistent. Substituting pozzolans for a portion of Portland cement enhances the concrete's resistance to aggressive environments, including exposure to acidic waters and chlorides. Today, various types of pozzolans derived from industrial and agro-industrial by-products are used to substitute cement, aiming to reduce energy consumption during clinker production and mitigate environmental impacts. These pozzolans, originally considered wastes without significant application, are now integral in minimizing costs and environmental effects in building material manufacturing. However, their effectiveness in cement mixtures remains a subject of scrutiny, necessitating detailed study of their properties and behaviors (Becerra-Duitama & Rojas-Avellaneda, 2022).

Wood Ash: Wood ash is a pozzolana. A pozzolana is a material rich in silica and alumina which in itself has little or no cementitious value but will, in finely divided form and in the presence of moisture, chemically react with calcium hydroxide at ordinary temperatures to form compounds possessing cementitious properties. Wood ash is a residual product formed through the combustion of wood (including sawdust, bark, branches, etc.) primarily for electricity generation. Temperatures for wood calcination typically range from 400°C to 1100°C. Pine and eucalyptus are the most common tree sources used in power plants, with hardwood, bark, and leaves also contributing significant ash amounts, typically recovering between 6% and 10% (Siddique, 2012). Approximately 70% of wood ash ends up in landfills, 20% is used as agricultural supplements, and 10% finds applications in construction, metal recovery, and pollution control. The physical and chemical properties crucial for its utilization depend on factors such as tree species, geographical origin, growth conditions, incineration method, and ash collection techniques.

Wood ash, a by-product of combustion in wood-fired plants and paper mills, serves as a pozzolanic material. As the use of wood for energy production increases, so will the availability of wood ash. This material is highly variable in composition, depending on the type of wood, combustion methods, and other factors like temperature and fuel purity (Siddique, 2012). WA is a product of wood combustion that possesses pozzolanic property. Several researchers had worked on partial replacement of cement in concrete with wood ash (Siddique et al., 2012). All the studies showed that addition of wood ash as partial replacement of cement has adverse effects on some features of concrete in terms of its compressive Strength and workability. Also, according to (Chowdhury et al., 2015), there was decrease in splitting tensile strength of WA concrete with increase in percentage of wood ash. These negative effects of partial replacement of cement with wood ash need to be tackled to maintain the integrity of the concrete (Raheem et al., 2019).

There are several ways shown to have improved pozzolans in concrete, some of which are: Nano silica, nanoparticles have been shown to improve concrete properties by creating a compact microstructure, which resulted in a decrease in permeability and enhanced mechanical properties. Nano Titanium (NT), Nazari et al. (2010) have carried out strength and water absorption coefficient evaluation of high performance self-compacted concrete. The results showed that the strength and water permeability resistance of the samples were improved by adding NT to the paste up to 4.0%, depending on increasing crystalline $Ca(OH)_2$ amount especially at the early age. Sodium Silicate (SS) Salt, a by-product of silicon metal production. It is non-toxic, non-corrosive and has low environmental impact whereby enhancing resistance to freeze-thaw cycles, sulfate attack and chemical attack in cement content.

Machine learning foundations in civil engineering: Algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting have proven effective for modelling complex datasets, particularly in predicting the compressive strength of concrete. For example, Chou et al. (2014) employed multi-national data analytics to forecast concrete strength using several ML techniques, demonstrating that ensemble methods significantly outperform traditional statistical approaches. Their study involved gathering a diverse dataset and applying multiple models, concluding that Random Forest yielded the most accurate predictions with minimal error.

Recent studies have further confirmed that ML models can effectively predict mechanical properties of concrete under different conditions. Kamolov (2023) provided a comprehensive review of various ML methods applied to analyze concrete properties, highlighting that models such as Gradient Boosting and Random Forest not only enhance prediction accuracy but also offer valuable insights into how different input parameters influence concrete performance. This body of work illustrates the transformative potential of ML in predictive modelling within the field of civil engineering.

Artificial Neural Networks (ANNs) are a category of machine learning models inspired by the structure and function of biological neural networks. They consist of interconnected nodes or neurons organized into layers: an input layer, one or more hidden layers, and an output layer. Each neuron processes incoming data using a weighted sum followed by a non-linear activation function, allowing the network to learn complex patterns within the data (Patterson and Gibson, 2017). In civil engineering contexts, ANNs have been widely utilized to predict concrete compressive strength based on various mix design parameters. Moreover, ANNs can adaptively learn from variations in data over time, making them well-suited for applications where material properties may change due to environmental factors or inconsistencies in materials. This adaptability is particularly advantageous when predicting concrete behavior under different loading conditions or environmental exposures.

The efficacy of DNNs heavily relies on hyperparameter selection, which includes determining factors such as the number of layers, nodes per layer, learning rate, batch size, and number of epochs. Each hyperparameter can significantly influence model performance; for instance, deeper networks may capture more intricate patterns but also require careful tuning to avoid overfitting (Patterson and Gibson, 2017).

Deep Neural Networks (DNNs) extend traditional ANNs by incorporating multiple hidden layers between the input and output layers. This increased depth enables DNNs to model complex relationships within large datasets more effectively than shallower networks (Patterson and Gibson, 2017). A DNN typically consists of several components: layers (input, hidden, output), nodes (neurons), activation functions (e.g., ReLU, sigmoid), and connections (weights). Training a DNN involves adjusting weights through backpropagation—a method where gradients of a loss function are calculated concerning each weight using the chain rule (Java point). This iterative process continues until the model converges on an optimal set of weights that minimize prediction error on training data while maintaining generalization capabilities on unseen data.

Sequence models like Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), and Long Short-Term Memory networks (LSTMs) are specifically designed for processing sequential data. RNNs utilize feedback loops that allow them to maintain information across sequences; however, they struggle with long-term dependencies due to vanishing gradient issues. Radial Basis Function Neural Networks (RBFNN) represent another type of neural network architecture that utilizes radial basis functions as activation functions. RBFNNs typically consist of three layers: an input layer, a hidden layer with RBF neurons, and an output layer. The hidden layer transforms inputs into a higher-dimensional space where linear separation becomes feasible. Principal Component Analysis (PCA) is a statistical technique used for dimensionality reduction while preserving as much variance as possible within high-dimensional datasets. By transforming correlated variables into uncorrelated principal components ranked by variance explained, PCA simplifies datasets without significant loss of information.

Long Short-Term Memory (LSTM) is a type of deep neural network that is designed to capture historical information of time series data and is suitable for predicting long-term nonlinear series. LSTM offers flexibility, improved memory performance, and ability to overcome problems associated with gradient dispersion. This architecture are capable of learning long-term dependencies in sequential data.

3. METHODOLOGY

This study entails the preparation of wood ash, laboratory tests on aggregates (fine and coarse) and wood ash, formwork fabrication, production of concrete specimens and mix proportioning, tests on concrete specimens. The ash was collected from the oven's exhaust post-combustion with the aid of hand scoop. This collection method ensured the absence of unburnt organic matter, which could negatively affect the concrete's properties. The samples were bagged in sacks and transported from the selected bread bakeries to the Laboratory sites where it was weighed and recorded. The wood ash was sieved to separate the ash from any unwanted material. The wood ash was passed through a 425µm sieve. The laboratory tests to be conducted on granite and river sand are sieve analysis and specific gravity. Tests conducted on River Sand, Granite Wood Ash, Fresh and Hardened Concrete are Sieve Analysis, Specific Gravity, X-ray Fluorescence Analysis, Aggregate Impact Value (AIV) Test, Slump Test, Compacting Factor Test, Density, Compressive Strength Test, Water Absorption. The form work was designed using Autodesk Inventor and AutoCAD software. This was made using marine board as a material for its build up. It was dimensioned to the required size of 150 by 150 by 150 [mm^3] cube size before taking to the saw mill for cutting into different parts of the mold with precision.

Concrete specimens were prepared by measuring the required quantities of cement, coarse aggregate, and fine aggregate in a 1:2:4 mix ratio, with a water-to-cement ratio of 0.6. The dry ingredients were thoroughly mixed by hand, to ensure uniform distribution. All materials were brought to room temperature before mixing.

Six different mix proportions were prepared for this study:

i. (WA0NSS0): Control mix with no wood ash or sodium silicate,
ii. (WA10SS0): 10% replacement of cement with wood ash, and 0% sodium silicate,
iii. (WA10SS0.5): 10% replacement of cement with wood ash, and 0.5% sodium silicate,
iv. (WA10SS1.0): 10% replacement of cement with wood ash, and 1.0% sodium silicate,
v. (WA10SS1.5): 10% replacement of cement with wood ash, and 1.5% sodium silicate, and
vi. (WA10SS2.0): 10% replacement of cement with wood ash, and 2.0% sodium silicate.

The 10% WA replacement was used as it had been established that it was the optimum content for structural purposes (Raheem and Adenuga, 2013). Table 1 shows the mix proportion by weight of the materials in each sample.

Batching of the concrete was done by weighing for each of the concrete mix ratios of 1:2:4 at 0.6 water/cement ratio. The constituent ingredients were thoroughly mixed manually before potable water was added to produce fresh concrete. The mixing was in accordance with BS 1881-125:1986. The specimens were left to set for 24 hours. After demolding, the cubes were placed in a water curing tank to ensure proper hydration. Curing was carried out at 25°C for periods of 7, 14, 28 and 56 days to monitor the development of strength over time. Tests carried out on the concrete specimens are slump test, compacting factor test, density test, compressive strength test, water absorption test.

Predicting compressive strength using LSTM networks: This report outlines the methodology employed in the project titled "Prediction of Compressive Strength with Long Short Term Memory Networks," which extends the findings from the previous work on the influence of sodium silicate on wood ash blended cement concrete. The focus here is on the deep learning aspect, specifically utilizing Long Short Term Memory (LSTM) networks for predicting compressive strength. The procedures includes: Data Preparation, Model Architecture, Loss Function, Training Procedure, Training Loop, Testing Procedure.

Table 1. Proportioning of Concrete

Sample	Percentage of SS (%)	Cement (kg)	Wood Ash (WA) (kg)	Fine Aggregates (FA) (kg)	Coarse Aggregates (CA) (kg)	Sodium Silicate (SS) (kg)
WA0SS0 (REF)	0	16.00	0	32	64	0
WA10SS0	0	14.40	1.6	32	64	0
WA10SS0.5	0.5	14.32	1.6	32	64	0.08
WA10SS1.0	1.0	14.24	1.6	32	64	0.16
WA10SS1.5	1.5	14.16	1.6	32	64	0.24
WA10SS2.0	2.0	14.08	1.6	32	64	0.32

The testing phase involved evaluating model performance on a separate test dataset comprising 24 samples. Similar to training, predictions were made using the model's forward pass, followed by loss calculation using Mean Absolute Percentage Error MAPE. Additional metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) were computed for comprehensive evaluation:

i. **RMSE**

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad 3.1$$

ii. **MAE:**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad 3.2$$

iii. **R^2 SCORE:**

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \quad 3.3$$

Where: $\bar{y}_i$ is the mean of actual values, y_i is the actual value, $\hat{y}_i$ is the predicted value, n is the number of observations. The training was conducted on a T4 GPU, which provided substantial computational power necessary for processing large datasets and complex model architectures efficiently.

4. RESULTS

Material characteristics: The physical properties of the aggregates used in this study are presented in Fig. 1. The coefficient of uniformity (Cu) and coefficient of curvature (Cc) for the coarse aggregate (granite), fine aggregate (river sand), and wood ash were determined according to ASTM C136. The Cu values were 4.21, 4.25, and 2.06, respectively, indicating that the fine aggregate and wood ash were well-graded, while the wood ash was poorly graded. The Cc values of 1.83, 1.47, and 1.14 for the coarse aggregate (granite), fine aggregate, and wood ash, respectively, further confirmed the grading characteristics of the materials. The wood ash is still poorly graded as seen in the results.

Table 2 detailed the Average Impact Value (AIV) test. This was conducted on the coarse aggregate (granite) as per (BS 812-112:1990). The AIV crushing value was found to be 25%, which is within the acceptable limit of 30% for concrete aggregates (BS 812-112:1990).

The specific gravity of the fine aggregate (river sand) is 2.73, while that of the wood ash is 2.35. The Tables 3 and 4 show the specific gravity of river sand and wood ash, respectively. The specific gravity of the fine aggregates and wood ash are within the standards of ASTM C33.

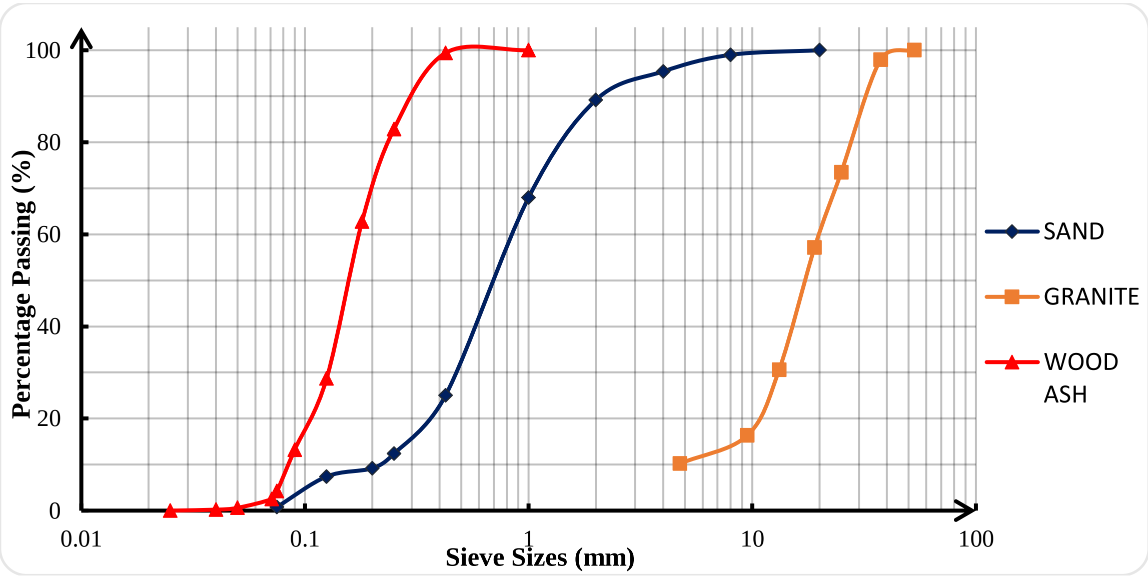

Fig. 1. Particle Size Distribution Curve

Table 2. Aggregate Impact Value Test (AIV)

Parameters	Mass
Mass of Crushed Stones, (W_1)	0.6kg
Mass of Crushed Stones sieved through 2.36mm sieve size, (W_2)	0.15kg
AIV Crushing Value	**25%**

Table 3. Specific Gravity of Fine Aggregates (River Sand)

	Trial 1	Trial 2	Average
Mass of density bottle(g), (W_1)	139.3	146.3	142.8
Mass of Density bottle +Wood ash (g), (W_2)	239.3	245.3	242.3
Mass of Density bottle + Wood ash + Water (g), (W_3)	503.1	503.1	503.1
Mass of Density bottle + Water (g), (W_4)	440.1	440.1	440.1
Specific Gravity	**2.70**	**2.75**	**2.73**

Table 4. Specific Gravity of Wood ash

	Trial 1	Trial 2	Average
Mass of density bottle(g), (W_1)	169.1	169.1	169.1
Mass of Density bottle +Wood ash (g), (W_2)	269.1	269.1	269.1
Mass of Density bottle + Wood ash + Water (g), (W_3)	808.0	807.4	807.7
Mass of Density bottle + Water (g), (W_4)	749.3	751.4	750.4
Specific Gravity	**2.42**	**2.27**	**2.35**

Table 5. Chemical Composition of Wood Ash

S/N	Formulae	% Composition
1	SiO_2	20.79
2	Al_2O_3	4.18
3	MgO	7.58
4	CaO	49.32
5	Fe_2O_3	3.10
6	K_2O	5.42
7	Na_2O	0.07
8	P_2O_5	3.28
9	TiO_2	0.06
10	MnO	1.63
11	NiO	0.01
12	ZnO	0.08
13	CuO	0.01
14	SO_3	1.30
15	LOI	3.17

Chemical composition (XRF Test) of wood ash: The chemical composition of the wood ash used in this study was determined using X-Ray Fluorescence (XRF) analysis, and the results are presented in Table 5. The wood ash was found to be rich in calcium oxide (CaO) at 49.32%, followed by silicon oxide (SiO_2) at 20.79%, magnesium oxide (MgO) at 7.58%, and potassium oxide (K_2O) at 5.42%. The high calcium content in the wood ash suggests its potential as a partial cement replacement material, as calcium is the primary constituent of Portland cement (Albassrih & Abbas, 2022). The presence of other oxides, such as aluminum oxide (Al_2O_3), iron oxide (Fe_2O_3), and phosphorus oxide (P_2O_5), may also contribute to the pozzolanic reactivity of the wood ash (Pathak & Siddique, 2012). The result shows that the wood ash is Class C Fly Ash because it contains more than 20% of CaO. This entails the primary presence of calcium alumino-sulfate glass, as well quartz, tricalcium aluminate, and free lime (CaO).

Concrete characteristics: The Concrete characteristics include: slump, compacting factor, density, compressive strength, and water absorption.

Workability: The slump and compacting factor values of the concrete mixtures are presented in Figs. 2 and 3 respectively. The reference mixture (WA0SS0) had a slump of 60 mm and a compacting factor of 0.94, indicating a medium workability. The addition of 10% wood ash without sodium silicate (WA10SS0) increased the slump to 115 mm, indicating a high workability. However, the addition of sodium silicate gradually decreased the slump, with the WA10SS1.0 mixture having the lowest slump of 20 mm, indicating a low workability. The compacting factor values ranged from 0.90 to 0.99, indicating that all the concrete mixtures were easily compactable.

The increase in slump with the addition of 10% wood ash can be attributed to the spherical shape and smooth surface of the wood ash particles, which can improve the flowability of the concrete mixture (Rashad, 2014). The decrease in slump with the increase in sodium silicate content which gave true slump values can be explained by the water-reducing and setting-accelerating properties of sodium silicate, which can result in a stiffer concrete mixture (Rashad, 2014).

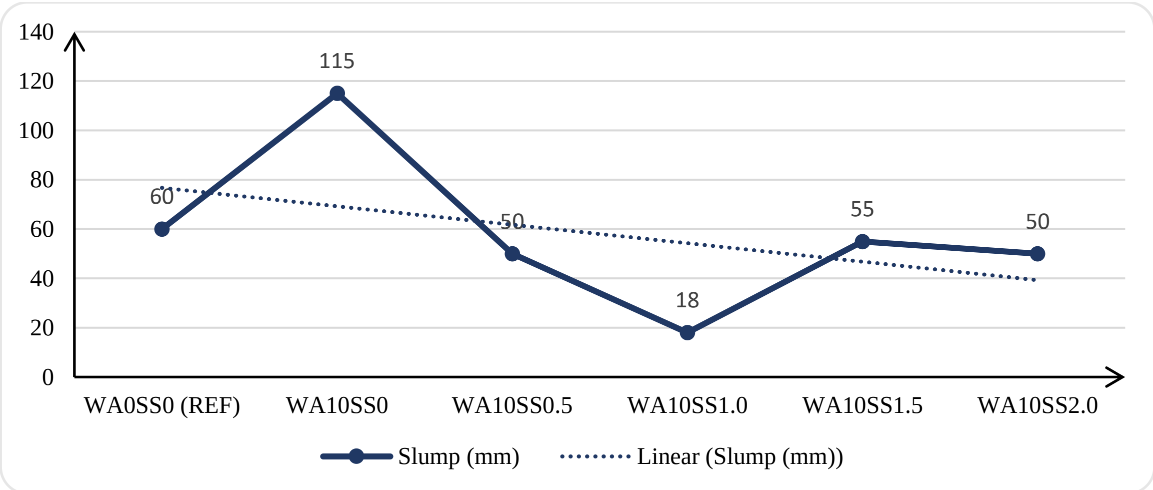

Fig. 2. Slump Test of Wood Ash Blended Cement Concrete

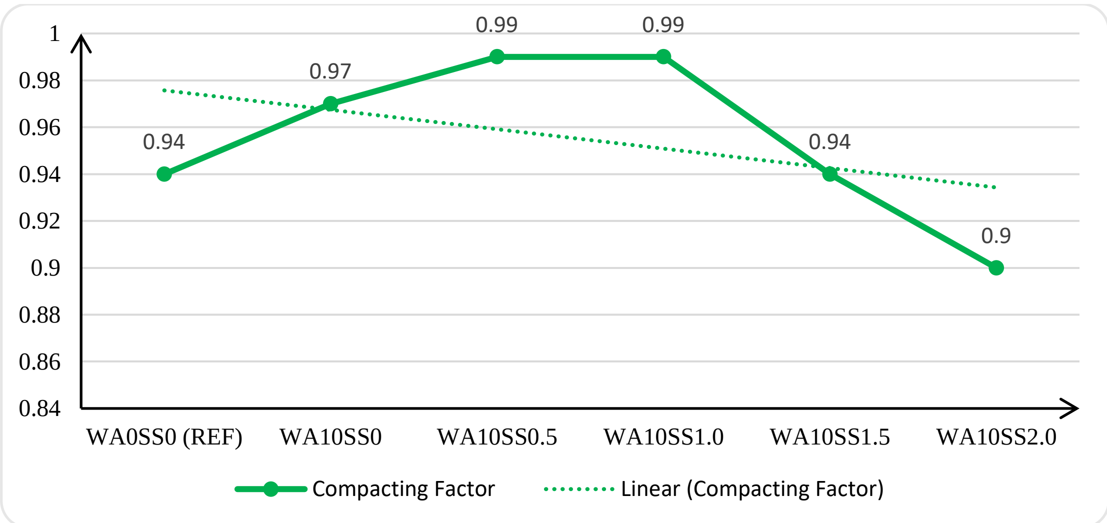

Fig. 3. Compacting Factor of Wood Ash Blended Cement Concrete

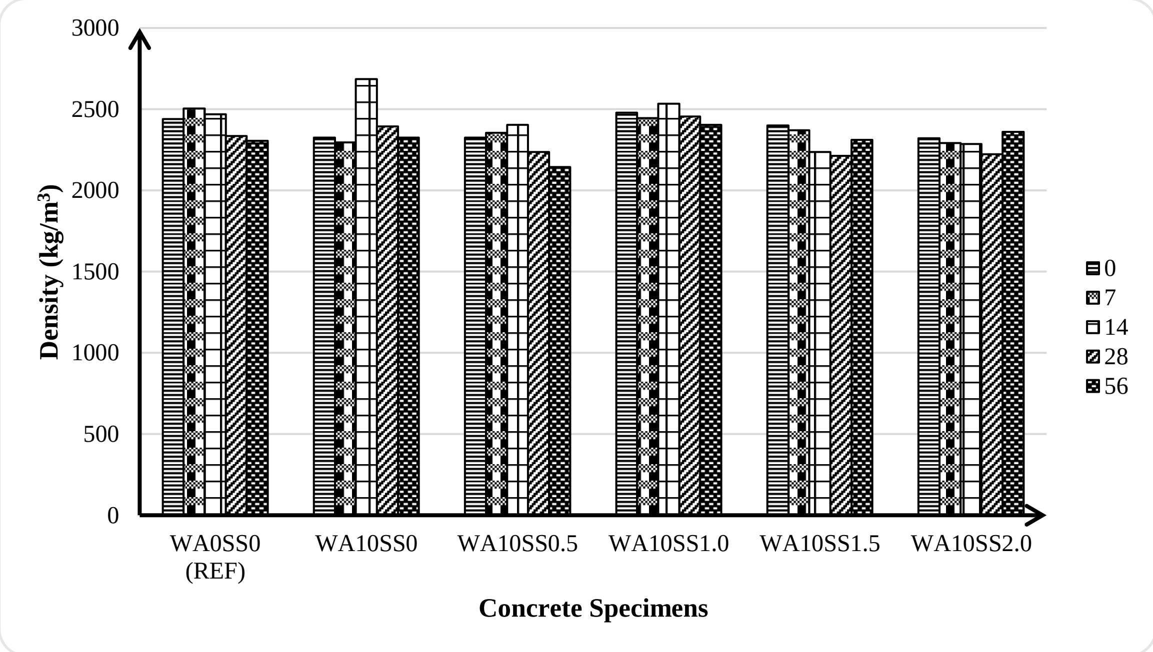

Fig. 4. Density of Wood Ash Blended Cement Concrete

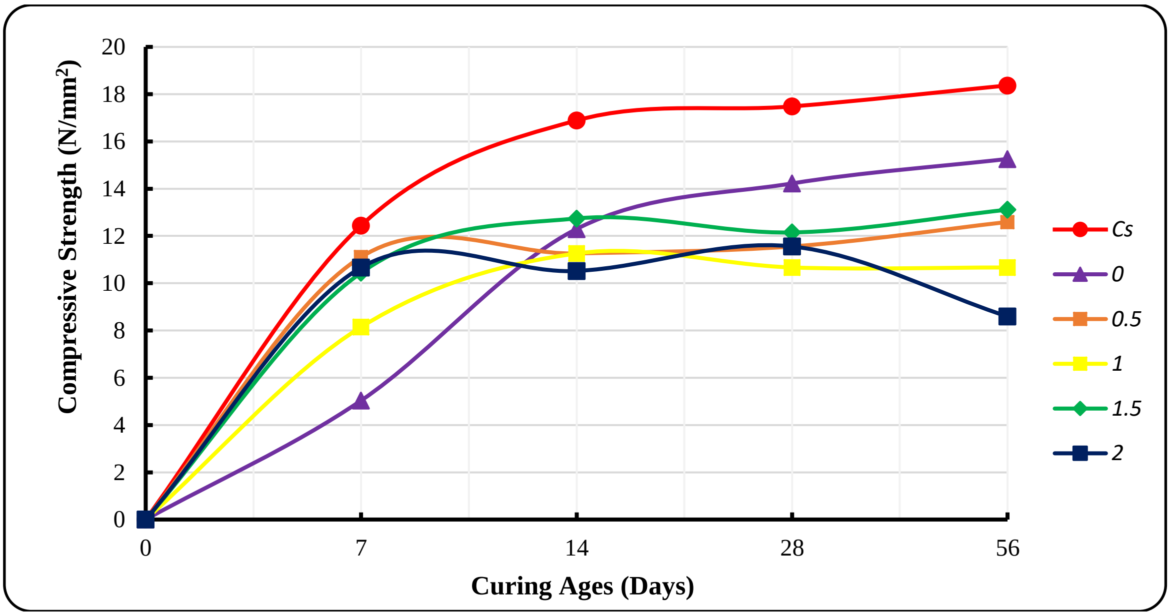

Fig. 5. Compressive Strength of Wood Ash Blended Cement Concrete

Density: The density values of the concrete mixtures at various curing ages are summarized in Fig. 4. The reference mixture (WA0SS0) exhibited a density of 2439.51 kg/m³ at 0 days, decreasing to 2306.17 kg/m³ by 56 days.

In contrast, the control mixture with 10% wood ash (WA10SS0) demonstrated a higher density than the reference, ranging from 2325.94 kg/m³ at 0 days to 2508.64 kg/m³ at 56 days, indicating superior packing efficiency. This finding is consistent with Kwan et al. (2014), who noted that finer particles can enhance packing density.

The incorporation of 10% wood ash along with varying proportions of sodium silicate yielded diverse density outcomes. The sodium silicate replacement (WA10SS0.5) recorded the lowest density, starting at 2325.93 kg/m³ at 0 days and dropping to 2143.21 kg/m³ at 56 days.

Conversely, WA10SS1.0 showed a density range of 2479.01 kg/m³ at 0 days to 2404.94 kg/m³ at 56 days, suggesting that higher sodium silicate content may counteract density loss. Density values for WA10SS1.5 and WA10SS2.0 fluctuated between 2400 kg/m³ to 2311.11 kg/m³ and 2321 kg/m³ to 2360.49 kg/m³, respectively, indicating a complex interaction between wood ash and sodium silicate. The observed reduction in density with increased sodium silicate suggests that its presence increases the volume of voids filled with cement paste, which diminishes overall packing density.

Compressive strength: Fig. 5 shows the compressive strength of the concrete specimens. (WA10SS0.5) gives a compressive strength of 11.11N/mm² at 7 days, and (WA10SS2.0) gives a compressive strength of 12.7 N/mm² at 14 days.

Sodium Silicate (SS) can absorb significant amounts of water, promoting faster hydration and enhancing the formation of hydration products, which contributes to early strength development. By dissolving in the pore water between cement particles, SS initiates a trigger effect, accelerating the setting process as calcium silicate hydrate (C-S-H) forms, resulting in rapid hardening (Cavusoglu et al., 2021). Kanagaraj et al. (2022) also presents this during the performance evaluation on engineering properties of sodium silicate binder as a precursor material for the development of cement-free concrete.

Water absorption: The water absorption values of the concrete mixtures at 28 days of curing are presented in Fig. 6. The reference mixture (WA0SS0) had a water absorption of 5.26%, while the control mixture without sodium silicate (WA0SS0) had a higher water absorption of 11.11%.

The addition of 10% wood ash and varying percentages of sodium silicate resulted in a range of water absorption values. The 0.5% sodium silicate replacement (WA10SS0.5) had a water absorption of 3.78%, while the 1.0% sodium silicate replacement (WA10SS1.0) had the lowest water absorption of 1.82%. The 1.5% and 2.0% sodium silicate replacements (WA10SS1.5 and WA10SS2.0) had water absorption values of 3.75% and 2.02%, respectively.

The decrease in water absorption with the addition of sodium silicate can be attributed to the pore-filling and pore-refinement properties of sodium silicate, which can lead to a denser and less permeable concrete matrix (Mehta et al., 2020). The higher water absorption of the control mixture without sodium silicate can be explained by the increased porosity and reduced packing efficiency of the concrete mixture due to the presence of wood ash alone.

Long short term memory model (LSTM): The LSTM is a type of RNN aimed at mitigating the vanishing gradient problem. The LSTM was characterized, trained, and the results were tested.

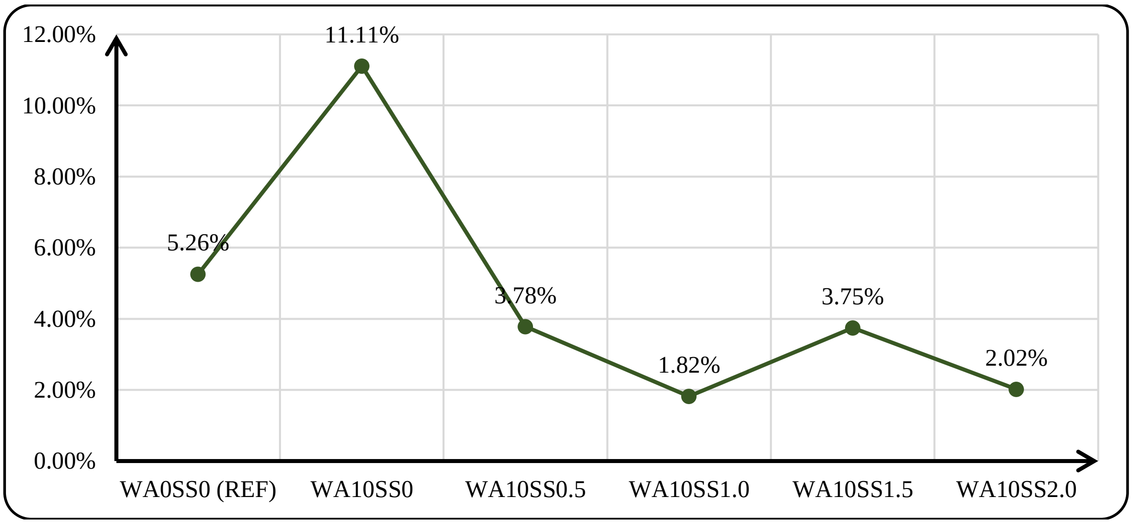

Fig. 6. Water Absorption of Wood Ash Blended Cement Concrete

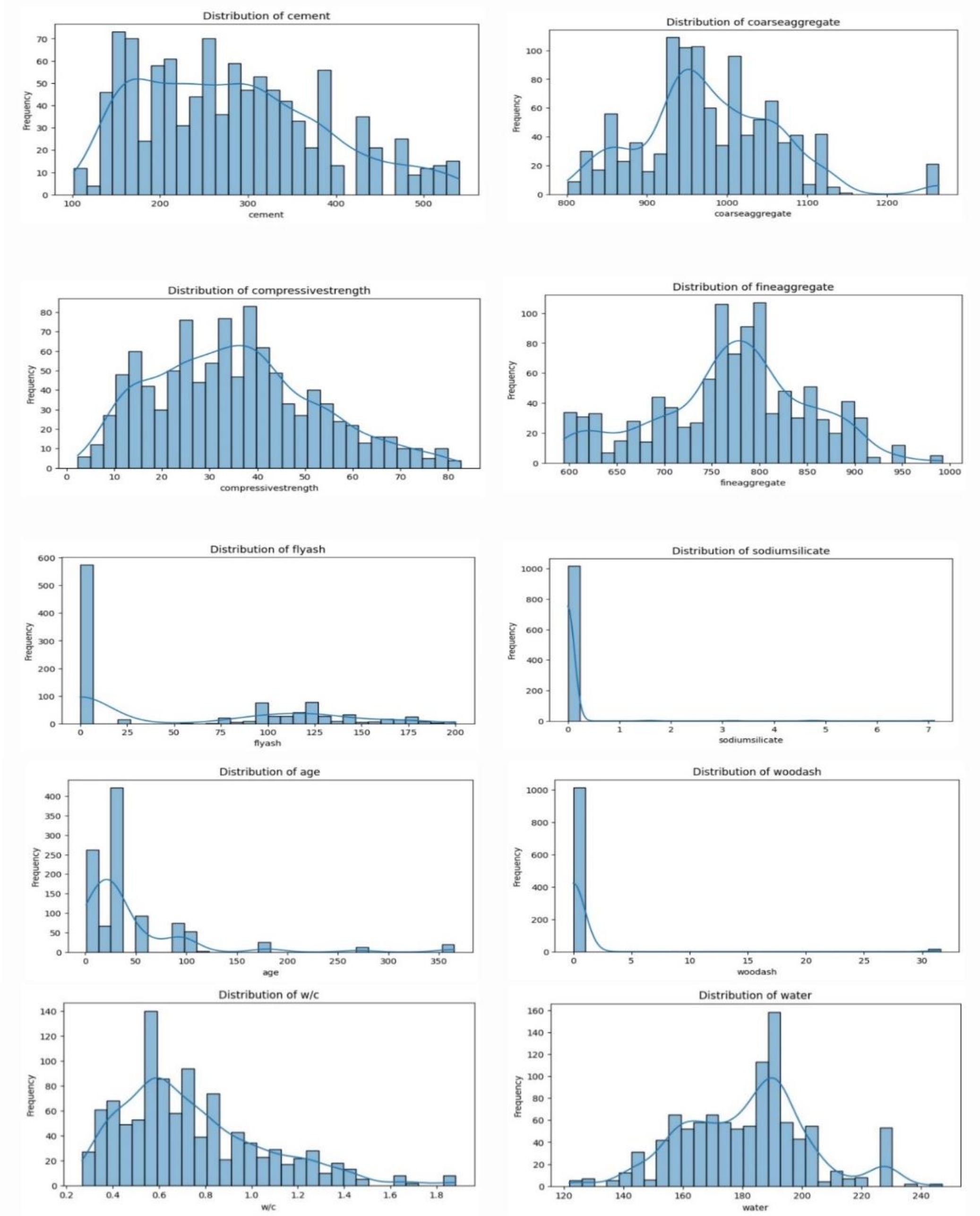

Fig. 7. Distribution plots for each parameter

Characteristics of the sourced data: The dataset used for training the LSTM model consists of various components relevant to the prediction of compressive strength in concrete mixtures. The statistical summary of the data, as provided by the `dataframe. describe ()` method, indicates significant variability in the parameters, which is crucial for effective model training.

The distribution plots for each parameter in Fig. 7 reveal that most features are normally distributed, with some skewness observed in parameters like water and sodium silicate, indicating their potential influence on compressive strength through varying mix designs.

In the initial epochs (1-5), the average loss decreased from approximately 91.31 to about 48.74, demonstrating rapid learning as the model adjusted weights based on input data, fluctuations in loss values were observed across batches within each epoch. By epoch three, average loss values had stabilized around the

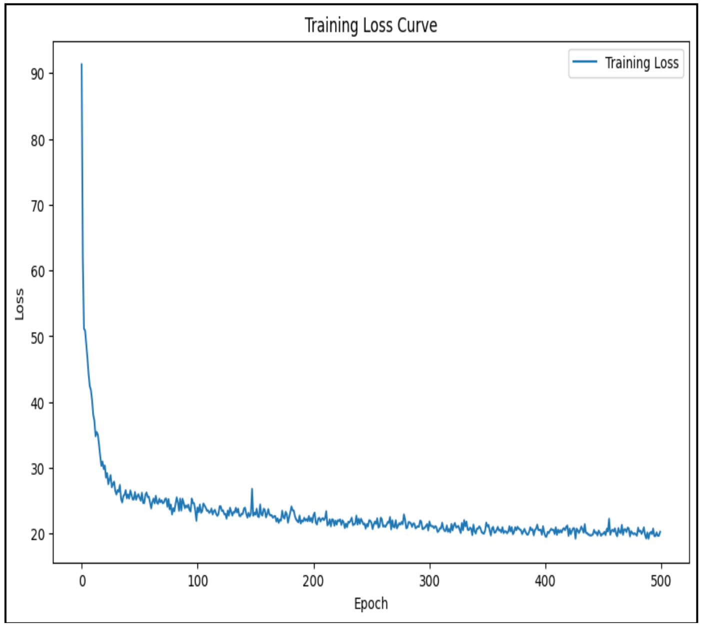

Fig. 8. Training Loss per epoch curve

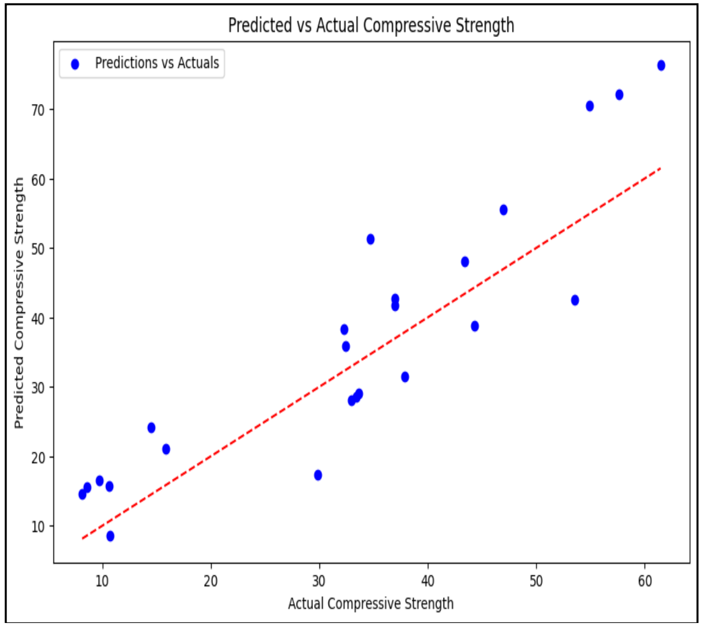

Fig. 9. Predicted vs Actual Compressive Strength

mid-50s range before further decreasing in subsequent epochs, reflecting improved predictive accuracy as the model converged. The loss curve plots in Figs. 8 and 9 indicated a consistent reduction in training loss, confirming that the LSTM model effectively learned from the training data over time.

Testing results: Upon evaluating the model with the test set comprising of 24 samples, the final test loss was recorded at approximately 31.04, The RMSE was recorded at approximately 8.80. MAE, at approximately 7.79, this metric further corroborates the RMSE findings. The R^2 value of approximately 0.70 suggests that about 70% of the variance in compressive strength can be explained by the model's inputs.

5. DISCUSSION

The results of this study demonstrate the potential of using wood ash and sodium silicate as partial replacements for cement in concrete. The characterization of the materials showed that the wood ash had high calcium content, which can contribute to the pozzolanic reactivity of the material. The particle size distribution analysis indicated that fine aggregate (river sand) and coarse aggregate (granite) were well-graded, while the wood ash was poorly graded.

The addition of 10% wood ash without sodium silicate increased the workability of the concrete, as evidenced by the higher slump values. This can be attributed to the spherical shape and smooth surface of the wood ash particles, which can improve the flowability of the concrete mixture. However, the addition of sodium silicate gradually decreased the slump, indicating a reduction in workability. This can be explained by the water-reducing and setting-accelerating properties of sodium silicate, which can result in a stiffer concrete mixture.

The density of the concrete mixtures was influenced by the addition of wood ash and sodium silicate. The decrease in density with the increase in wood ash content can be attributed to the lower specific gravity of wood ash compared to cement. The increase in density with the addition of sodium silicate can be explained by the ability of sodium silicate to enhance the hydration and packing of the concrete mixture, leading to a denser microstructure.

The water absorption of the concrete mixtures was also affected by the addition of wood ash and sodium silicate, The decrease in water absorption with the addition of sodium silicate can be attributed to the pore-filling and pore-refinement properties of sodium silicate, which can lead to a denser and less permeable concrete matrix. The higher water absorption of the control mixture without sodium silicate can be explained by the increased porosity and reduced packing efficiency of the concrete mixture due to the presence of wood ash alone. The results of this study are consistent with the findings of previous research on the use of fly ash and sodium silicate in concrete For example, a study by Karthika, (2018) reported that the addition of fly ash as a partial cement replacement can improve its compatibility and reduce the water absorption of concrete, while enhancing the early compressive strength and durability properties of concrete.

Comparative analysis with existing literature (Alsharif and Alzahrani, 2019; Akinwumi and Ojo, 2020) reveals that while many studies report R^2 values ranging from 0.60 to above for similar predictive tasks using traditional regression methods or simpler neural networks, this LSTM approach yielded competitive results despite its complexity and higher computational requirements. Notably, some studies Sahu and Kumar, 2021 have reported higher R^2 values (>0.80) using advanced techniques such as ensemble methods or hybrid models combining different machine learning algorithms; however, these often require more extensive datasets or additional feature engineering efforts.

6. CONCLUSION AND RECOMMENDATION

This study investigated the influence of sodium silicate on the properties of wood ash blended cement concrete. The following are the conclusions:

i. The sand and granite were characterized to be well-graded, while wood ash was characterized to be poorly-graded. The wood ash is a class C fly ash.
ii. Wood Ash Blended Cement Concrete specimens with Sodium Silicate has high early compressive strength, and reduction in density, water absorption, and workability rate.
iii. The Long Short Term Memory machine learning model gave a valuable insight into

the reliable measurement of concrete compressive strength with given concrete parameter as inputs.

Based on the findings of this study, the following recommendations are made:

i. The blended cement concrete developed is applicable as rapid repair patching material in temporal or emergency repairs for concrete surfaces that will later be replaced or reinforced; serve as a quick fix without a long term commitment to strength.
ii. It is also applicable for use in sidewalks, walkways, or other low-load areas where traffic is minimal and longevity isn't critical.
iii. Further research should be conducted on long-term performance, curing methods, and strength optimization of wood ash blended cement concrete with sodium silicate under varied environmental conditions.
iv. Again, future research should focus on optimizing the proportions of wood ash and sodium silicate and results for longer curing days to maximize both economic benefits and mechanical properties. Developing predictive models using machine learning techniques could facilitate this optimization process.
v. Finally, it is desirable that a study should be conducted to establish further exploration on more pozzolanic materials and incorporation of high content properties salt in terms of enhanced compressive strength in concrete.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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