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Research paper

Artificial Intelligence & Quantum Computing for Causal Loop and Chronology Violation Detection:
A Deep Learning Approach to Predicting Traversable Wormhole Stability and Temporal Paradoxes

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KEYWORDS

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Wormhole Stability Prediction
Chronology Protection Mechanisms
Closed Timelike Curves (CTCs)
Physics-Informed Neural Networks (PINNs)

ABSTRACT

As admissible solutions to Einstein's field equations, traversable wormholes present the prospect of non-trivial topological structures tying disparate areas of spacetime together. Their stability is seriously questioned because their theoretical existence, which is determined by the Morris-Thorne metric, requires the inclusion of exotic matter that violates the energy conditions. These structures also allow for the creation of closed timelike curves (CTCs), which could violate causality and cause paradoxes, undermining the basic tenets of chronology protection. Although different gravity models and semiclassical quantum effects suggest ways to maintain wormholes, it is still unclear how to precisely formulate stability criteria and causal consistency. In order to predict wormhole stability and identify the emergence of causal loops, this study makes use of deep learning techniques and artificial intelligence (AI). In order to evaluate the effect of exotic matter distributions on stability, Einstein's field equations are numerically solved using Physics-Informed Neural Networks (PINNs) under dynamic boundary conditions. Potential CTC formations and self-consistency violations are detected by tracing geodesic structures using Graph Neural Networks (GNNs), Quantum Neural Network (QNNs)and Recurrent Neural Networks (RNNs). Furthermore, the exotic matter configuration is optimised via reinforcement learning (RL) techniques to minimise instabilities while maintaining traversability. This research advances the intersection of machine learning, general relativity, and quantum field theory in the study of spacetime topology and causality, analyses chronology protection mechanisms, and evaluates wormhole viability by fusing relativistic physics with AI-driven computational techniques.

1. Introduction

The Morris-Thorne metric offers a mathematical framework for describing such structures, ensuring traversability without event horizons. Traversable wormholes, first theorised within general relativity, offer

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hypothetical shortcuts through spacetime, potentially enabling faster-than-light travel and even time travel. However, maintaining a stable wormhole requires exotic matter that violates known energy conditions, specifically the Null Energy Condition (NEC). This requirement presents significant theoretical and physical challenges, as exotic matter remains speculative with no verified natural sources (Radhakrishnan, R. et al., 2024).

Beyond stability, traversable wormholes present serious issues with chronology protection and causality. These structures contain closed timelike curves (CTCs), which raise the possibility of time travel and give rise to paradoxes like self-referential causal loops and the grandfather paradox. In response, Hawking's Chronology Protection Conjecture suggests that by destabilising CTC production, quantum processes might stop such violations. However, there are still unanswered problems regarding the basic structure of spacetime because a definitive mechanism enforcing this conjecture has not been proven (Youvan, Douglas. 2024).

Deep learning (DL) and artificial intelligence (AI) provide strong computational tools for examining wormhole stability and causality violations because of their complexity. In order to forecast stability under various exotic matter conditions, this study uses deep learning frameworks like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in conjunction with AI-driven numerical relativity simulations to describe wormhole dynamics (Reyna, Joseph, 2024).

Neural networks are used to detect CTC evolution and analyse geodesic structures in order to evaluate causality violations. In order to find any self-consistency violations, graph neural networks (GNNs) look into the causal structure of spacetime in more detail. Furthermore, to determine if quantum effects strengthen chronology protection, AI-driven quantum simulations assess vacuum fluctuations and energy density limitations (Samar Hadou et al., 2021).

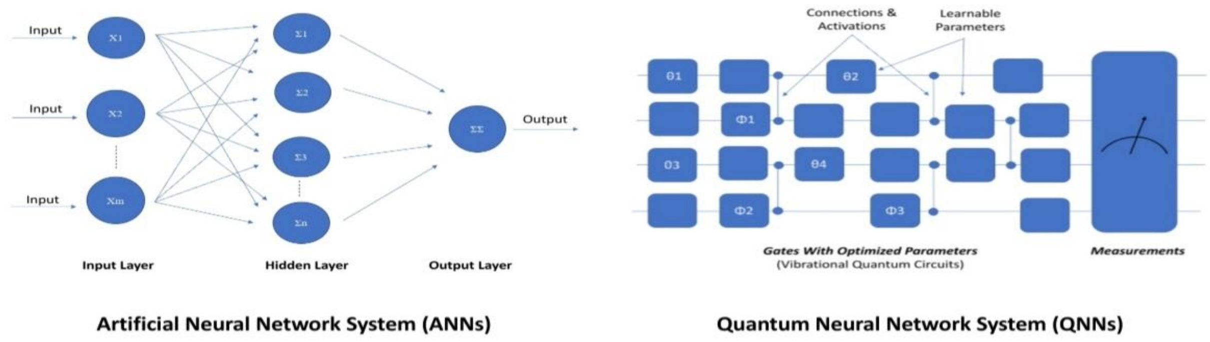

Fig. 1 Fundamental & Basic unit of Artificial Neural Network System (ANNs) & Quantum Neural Network System (QNNs)

This study intends to offer a computational framework for comprehending the viability of traversable wormholes, the stability issues raised by exotic matter, and the consequences of causality violations by fusing AI with relativistic physics. The results could further the investigation of quantum gravity, spacetime topology, and the basic boundaries of time manipulation and faster-than-light travel.

2. Theoretical Framework

2.1 Traversable Wormholes in General Relativity

Einstein's Field Equations (EFEs), which describe non-trivial topological structures connecting two different areas of spacetime, include hypothetical solutions known as traversable wormholes. Such solutions, which were first proposed in the framework of general relativity, necessitate the existence of exotic matter, which defies accepted energy conditions and poses serious stability issues.

<u>Einstein's Field Equations and Wormhole Solutions</u>

The Einstein field equations are given by:

$$G_{\mu\nu} + \Lambda g_{\mu\nu} = (8\pi G/c^4)\, T_{\mu\nu}$$

Where $G_{\mu\nu}$ represents the Einstein tensor, Λ is the cosmological constant, $g_{\mu\nu}$ is the metric tensor, and $T_{\mu\nu}$ is the stress-energy tensor. For a wormhole to be a valid solution, the metric must allow traversability, meaning an observer can pass through without encountering singularities or event horizons (Galina Weinstein. 2013).

Morris-Thorne Metric and Throat Conditions

The most widely studied traversable wormhole solution is the Morris-Thorne metric, expressed as:

$$ds^2 = -c^2\, dt^2 + (dr^2 / (1 - b(r)/r)) + r^2\, (d\theta^2 + \sin^2\theta\, d\varphi^2)$$

Where $b(r)$ is the shape function that determines the wormhole geometry. The throat of the wormhole is defined at the minimum radius r_0, where $b(r_0) = r_0$, ensuring the structure remains open for traversal. The critical condition for traversability is flare-out, requiring that:

$$b'(r_o) < 1R$$

Which necessitates the presence of exotic matter to satisfy the required spacetime curvature (Lemos, José 2003).

Stability Conditions and Energy Constraints

Wormhole stability depends on the behavior of the stress-energy tensor, which is governed by various energy conditions:

Null Energy Condition (NEC): $T_{\mu\nu}\, k^\mu\, k^\nu \geq 0$ *(violated for exotic matter).*
Weak Energy Condition (WEC): $T_{\mu\nu}\, u^\mu\, u^\nu \geq 0$ *(ensures positivity of energy density).*
Dominant Energy Condition (DEC): $T_{\mu\nu}\, u^\mu\, u^\nu \geq 0$ *with energy flow timelike or null.*
Strong Energy Condition (SEC): $(T_{\mu\nu} - \frac{1}{2} g_{\mu\nu}\, T)\, u^\mu\, u^\nu \geq 0$ *(often violated in wormhole solutions) (Kontou, E.-A. 2024).*

Additionally, stability analysis incorporates the Raychaudhuri equation, which describes the evolution of geodesic congruences:

$$(d\theta/d\tau) = -(1/3)\,\theta^2 - \sigma_{\mu\nu}\sigma_{\mu\nu} + \omega_{\mu\nu}\omega^{\mu\nu} - R_{\mu\nu}\, u^\mu\, u^\nu$$

Where θ represents expansion, $\sigma_{\mu\nu}$ is the shear tensor, $\omega_{\mu\nu}$ is the vorticity, and $R_{\mu\nu}\, u^\mu\, u^\nu$ is the Ricci tensor contribution. For a stable traversable wormhole, expansion must remain non-negative, requiring the violation of NEC (Kar, S., & Sengupta, S. 2007).

Thus, the existence of stable, traversable wormholes remains an open challenge in general relativity, necessitating novel approaches such as AI-driven simulations to analyze their dynamics and stability conditions.

2.2 Closed Timelike Curves and Causal Loops

Formation of Closed Timelike Curves (CTCs) in Wormhole Solutions

Theoretically, a traversable wormhole might create closed timelike curves (CTCs), which would allow an item or observer to travel back in time. Classical ideas of causation are directly violated by this event. The spacetime metric, in which a timelike worldline creates a loop, is associated with the existence of CTCs. This is expressed mathematically as:

$$G_{\mu\nu}\, dx^\mu\, dx^\nu < 0$$

For a wormhole to develop CTCs, the two mouths must have a time difference that allows an observer to travel through one and exit in the past. If one mouth undergoes relativistic motion or exists in a different gravitational potential, time dilation effects can lead to non-trivial causal loops. This time difference can be expressed as:

$$\Delta\tau = \int(\text{mouth A to mouth B})\, \sqrt{g_{00}}\, dt$$

Where $\Delta\tau$ represents the proper time difference between the two wormhole mouths (Thorne, K. S. 1992).

Causality Violation and Temporal Paradoxes

The existence of CTCs leads to major causality paradoxes, including:

The Grandfather Paradox: A time traveler could go back and prevent their own existence, leading to a logical contradiction.

The Bootstrap Paradox: Information or objects could exist in a closed causal loop with no clear origin, violating information conservation laws.

These paradoxes can be analyzed using the Killing vector field $\xi\mu$, which determines whether a given trajectory is timelike or spacelike:

$$\xi^\mu = \partial/\partial t$$

If this vector field becomes spacelike $(g_{\mu\nu}\xi^\mu\xi^\mu > 0)$ in certain regions, it indicates a violation of causality, allowing for CTC formation (Sfetcu, Nicolae. 2019).

2.3 Self-Consistency Principles in Time Travel

To address these paradoxes, several self-consistency principles have been proposed:

Novikov's Self-Consistency Principle: Any event that would create a paradox has a probability of zero. Only self-consistent timelines can occur. This principle can be mathematically expressed as:

$$dP/dt = 0$$

where P represents the probability of an event occurring in a way that alters past conditions (Solnyshkov, D. D., & Malpuech, G. 2020).

Deutsch's Model in Quantum Mechanics: This theory suggests that quantum states evolve in a self-consistent manner when subjected to CTCs. The evolution of the density matrix ρ is given by:

$$\rho_{CTC} = Tr_{sys} (U\rho_{sys} \otimes \rho_{CTC}{}^{U}\dagger)$$

where U is the unitary evolution operator ensuring that quantum information remains consistent over time (Dejonghe, Richard. et al., 2009).

2.4 Hawking's Chronology Protection Conjecture

Stephen Hawking put forth the Chronology Protection Conjecture, which postulates that quantum processes inhibit the production of CTCs in order to avoid causality violations. This conjecture states that wormhole stability is disrupted by the enormous stress-energy generated by vacuum oscillations in quantum field theory close to CTC borders.

The expectation value of the stress-energy tensor in curved spacetime follows:

$$\langle T_{\mu\nu} \rangle \sim 1/r^4$$

Which diverges as $r \to 0$, preventing CTCs from forming. If this conjecture holds, then stable time machines via traversable wormholes are theoretically impossible, preserving global causality (Hawking, S. W. 1992).

2.5 AI in Theoretical Physics

Applications of Machine Learning in General Relativity and Quantum Mechanics

In theoretical and applied physics, machine learning (ML) has become a potent instrument that provides innovative solutions to challenging issues in quantum mechanics (QM) and general relativity (GR). ML-based approaches are a possible substitute for computationally costly traditional methods for solving Einstein's field equations and quantum wavefunctions (He, YH. 2024).

Physics-Informed Neural Networks (PINNs) for Solving Differential Equations

Solving the nonlinear differential equations governing spacetime geometry and quantum states is a major challenge in both GR and QM. A data-driven method for resolving such equations while taking physical restrictions into account is offered by Physics-Informed Neural Networks (PINNs) (He, YH. 2024).

2.6 Application in General Relativity

Einstein's field equations (EFEs) can be roughly solved by PINNs, especially in situations like near black hole singularities when numerical approaches are ineffective. They are helpful in forecasting the stability of traversable wormholes, where managing nonlinear equations is necessary to solve for exotic matter distributions.

A general form of Einstein's field equations solved using PINNs is:

$$G_{\mu\nu} + \Lambda g_{\mu\nu} = 8\pi T_{\mu\nu}$$

where $G_{\mu\nu}$ is the Einstein tensor, Λ is the cosmological constant, and $T_{\mu\nu}$ represents the stress-energy tensor. PINNs learn solutions by minimizing residuals in these equations (Durrani, Ijaz. (2024).

2.7 Application in Quantum Mechanics

PINNs have been applied to solve the Schrödinger equation, predicting energy eigenvalues and wavefunctions with high precision:

$$i\hbar\, (\partial\psi/\partial t) = \hat{H}\psi$$

Where ψ is the wavefunction and $\hat{H}$ is the Hamiltonian operator.

AI-Based Anomaly Detection in Physical Systems

AI and deep learning play a crucial role in detecting anomalies in complex physical systems, particularly in gravitational wave signals, black hole mergers, and quantum entanglement dynamics (Liam Harcombe, Quanling Deng, et al. 2023).

Table 1 Overview of Theoretical Framework of Traversable Wormholes, Causality, and AI in Theoretical Physics

Section	Topic	Key Concepts	Mathematical Representation	References
Traversable Wormholes in General Relativity	Einstein's Field Equations (EFEs)	Einstein's Field Equations (EFEs), exotic matter, traversability conditions	$G_{\mu\nu} + \Lambda_{g\mu\nu} = (8\pi G/c^4)\ T_{\mu\nu}$	Galina Weinstein (2013)
	Morris-Thorne Metric	Shape function b(r), throat condition r_0, flare-out condition	$Ds^2 = -c^2\ dt^2 + (dr^2 / (1 - b(r)/r)) + r^2\ (d\theta^2 + \sin^2\theta\ d\varphi^2)$	Lemos, José (2003)
	Stability and Energy Conditions	NEC, WEC, DEC, SEC, Raychaudhuri equation	$(d\theta/d\tau) = -(1/3)\ \theta^2 - \sigma_{\mu\nu}\sigma_{\mu\nu} + \omega^{\mu\nu}\omega^{\mu\nu} - R_{\mu\nu}\ u^\mu\ u^\nu$	Kontou, E.-A. (2024); Kar, S., & Sengupta, S. (2007)
Closed Timelike Curves (CTCs) and Causal Loops	Formation of Closed Timelike Curves (CTCs) and Causal Loops	Time travel, causality violation, time dilation effects	$\Delta_\tau = \int(\text{mouth A to mouth B})\ \sqrt{g_{00}}\ dt$	Thorne, K. S. (1992)
	Causality Paradoxes	Grandfather paradox, bootstrap paradox, Killing vector field	$\xi^\mu = \partial/\partial t$	Sfetcu, Nicolae (2019)
Self Consistency Principles in Time Travel	Novikov's Self-Consistency Principle	Any paradox-creating event has zero probability	$dP/dt = 0$	Solnyshkov, D. D., & Malpuech, G. (2020)
	Deutsch's Quantum Model	Quantum state evolution in CTCs, unitary transformations	$\rho_{CTC} = Tr_{sys}\ (U\rho_{sys} \otimes \rho_{CTC}{}^{U}\dagger)$	Dejonghe, Richard et al. (2009)
Hawking's Conjecture	Hawking's Chronology Protection Conjecture	Prevention of CTCs, vacuum fluctuations, stress-energy divergence	$\langle T_{\mu\nu}\rangle \sim 1/r^4$	Hawking, S. W. (1992)
Synergy of AI & Physics	AI in Theoretical Physics	ML applications in general relativity and quantum mechanics	-	He, YH. (2024)
Physics Informed Neural Network System	PINNs for Solving Einstein's Equations	ML-based numerical solutions, stability predictions for wormholes	$G_{\mu\nu} + \Lambda g_{\mu\nu} = 8\pi T_{\mu\nu}$	Durrani, Ijaz. (2024)
Synergy of AI & Quantum Physics	AI in Quantum Mechanics	Solving Schrödinger equation, quantum state predictions	$i\hbar\ (\partial\psi/\partial t) = \hat{H}_\psi$	(Liam Harcombe, Quanling Deng, et al. 2023)

2.8 Future Directions

Integrating deep learning and symbolic physics into hybrid AI models to bridge the gap between AI and basic physics. Utilising quantum machine learning (QML) to accelerate calculations in spacetime modelling and quantum field theory. Speculating about new physics situations, such as unusual wormhole geometries and unique quantum states, using generative models. By providing computationally effective substitutes for conventional physics simulations, these AI-driven developments have the potential to completely transform our comprehension of spacetime, gravity, and quantum phenomena.

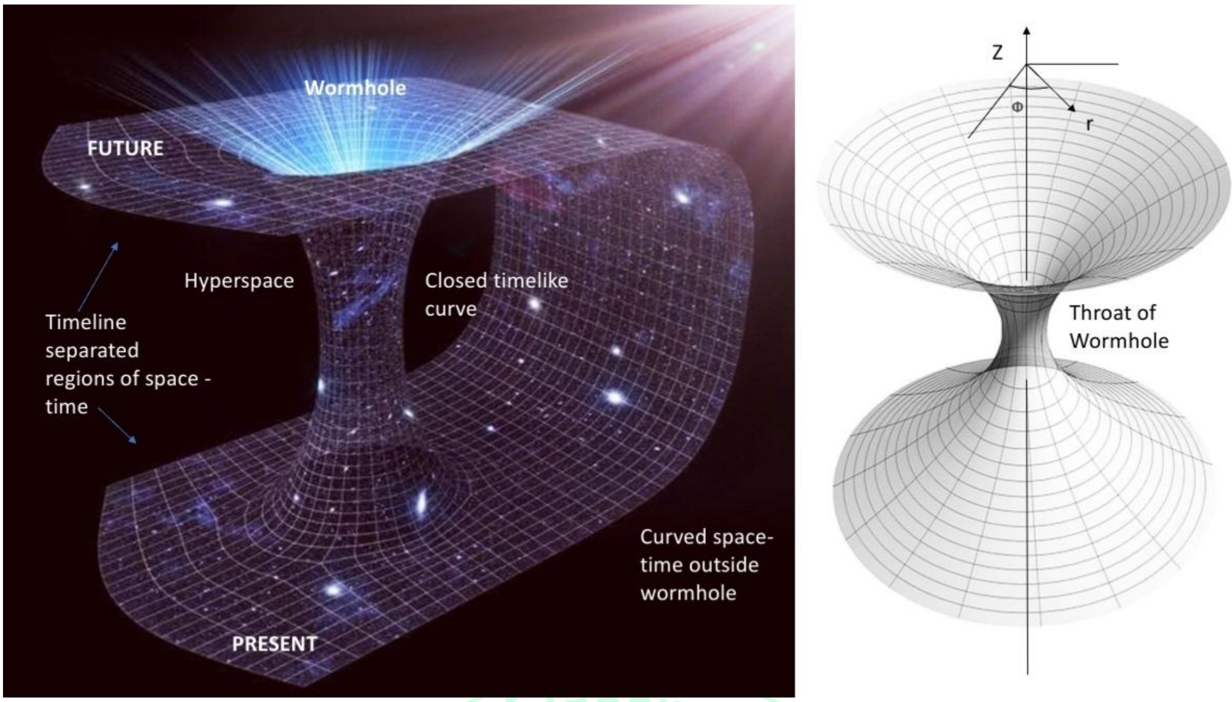

Fig. 2 Diagram of Generic Wormhole in Two Spatial Dimensions Embedded in Three Spatial Dimensions

3. Methodology

This study analyses wormhole stability, identifies causal loop violations, and investigates chronological protection strategies using deep learning, reinforcement learning, and graph neural networks. In order to investigate the viability of traversable wormholes and their implications for causality, AI-driven simulations integrate Einstein's field equations, quantum fluctuations, and spacetime geometry.

3.1 AI Model for Wormhole Stability Prediction

Deep Learning Model Architecture

A deep learning framework is developed to assess wormhole stability based on key physical parameters.

Input Features

- Stress-energy tensor components ($T_{\mu\nu}$)
- Curvature scalar (R)
- Exotic matter density (ρ_{exotic})
- Violations of energy conditions, including the Null Energy Condition (NEC), Weak Energy Condition (WEC), Dominant Energy Condition (DEC), and Strong Energy Condition (SEC)

Processing

Convolutional Neural Networks (CNNs): Extract spatial features from spacetime curvature tensors, modeling the structure of the wormhole throat.
Recurrent Neural Networks (RNNs): Analyze temporal dependencies in wormhole evolution to detect dynamic instability.

Output Predictions

Stability score ($S_{stability}$), computed as a function of CNN and RNN outputs:

$$S_{stability} = f_{CNN+RNN}(T_{\mu\nu}, R, \rho_{exotic})$$

- Throat collapse probability ($P_{collapse}$)
- Violation of energy conditions, indicating the presence of exotic matter

Reinforcement Learning for Stability Optimization

Reinforcement learning is applied to optimize negative energy distribution, improving wormhole stability.
State Space: Energy-momentum tensor configurations
Action Space: Adjustments to exotic matter distribution
Reward Function: Maximizing stability while minimizing the need for exotic matter, given by:

$$R = 1 / (1 + \Sigma |T_{\mu\nu} - T_{\mu\nu}^{optimal}|)$$

3.2 AI for Causal Loop and Paradox Detection

Temporal Geodesic Analysis Using Neural Networks

AI models use Einstein's geodesic equation to detect closed time like curves (CTCs) and causal anomalies:

$$d^2x^\mu / d\tau^2 + \Gamma^\mu_{\alpha\beta} (dx^\alpha / d\tau) (dx^\beta / d\tau) = 0$$

Neural networks predict geodesic behavior and identify when worldlines form closed loops.

Graph Neural Networks (GNNs) analyze causal structures in simulated spacetimes to detect violations of chronology protection.

The probability of CTC formation (PCTC) is calculated as a function of the metric tensor $g_{\mu\nu}$ and Christoffel symbols $\Gamma^\mu_{\alpha\beta}$:

$$P_{CTC} = f_{GNN}(g_{\mu\nu}, \Gamma^\mu_{\alpha\beta})$$

A high value of PCTC suggests potential causality violations, requiring further quantum backreaction analysis.

Self-Consistency Validation with AI

To examine time-travel paradoxes, AI-driven simulations integrate:

Novikov's Self-Consistency Principle: Ensuring that only logically consistent timelines emerge in AI-generated scenarios.

Quantum-Informed Machine Learning: Using probabilistic quantum models to analyze paradox resolution mechanisms.

The probability of a paradox-free solution $(P_{paradox\text{-}free})$ is given by:

$$P_{paradox\text{-}free} = \Sigma_i P_i e^{(-Si / \hbar)}$$

Where S_i represents the action integral contributions across different time-evolution pathways.

3.3 AI for Chronology Protection Mechanisms

This study explores AI-based detection of quantum fluctuations and vacuum energy densities that may prevent CTC formation, supporting Hawking's Chronology Protection Conjecture.

Quantum Fluctuation Detection

AI models simulate quantum vacuum fluctuations near wormhole throats to determine energy conditions that prevent time-travel loops.

Physics-Informed Neural Networks (PINNs) solve energy-momentum constraints to assess whether quantum effects destabilize CTC formation:

$$\langle T_{\mu\nu}\rangle_{ren} = f_{PINN}(\psi, g_{\mu\nu})$$

Where $\langle T_{\mu\nu}\rangle_{ren}$ represents the renormalized energy-momentum tensor influenced by vacuum fluctuations.

Simulating Energy Density Constraints

AI-driven Monte Carlo simulations analyze fluctuations in energy density at the wormhole throat.

These models evaluate whether quantum backreaction effects reinforce chronology protection by destabilizing CTCs.

This methodology examines chronology protection methods, analyses wormhole stability, and detects causal violations by combining deep learning, reinforcement learning, and quantum-informed AI. A computational foundation for comprehending the viability of time travel, traversable wormholes, and self-consistent spacetime evolution is offered by AI-driven simulations.

4. Experimental Setup & Computational Simulations

4.1 Numerical Relativity Simulations

This study uses AI-assisted numerical relativity simulations to predict wormhole stability and identify possible violations of causality. In order to dynamically describe the evolution of spacetime curvature, Einstein's Field Equations (EFEs) are solved using deep learning frameworks like TensorFlow and PyTorch combined with Physics-Informed Neural Networks (PINNs).

4.2 Implementation of EFEs Solvers using AI

Einstein's Field Equations and AI-Based Solvers

Einstein's Field Equations describe the relationship between spacetime curvature and the distribution of energy and momentum (Galina Weinstein. 2013):

$$G_{\mu\nu} + \Lambda g_{\mu\nu} = (8\pi G/c^4)\, T_{\mu\nu}$$

Where:

$G_{\mu\nu}$ represents the Einstein tensor, which encodes spacetime curvature.
Λ is the cosmological constant.
$T_{\mu\nu}$ is the stress-energy tensor.
G is the gravitational constant.
c is the speed of light.

In order to effectively forecast wormhole dynamics, AI-based solutions combine these equations utilising deep learning and automatic differentiation. Wormhole stability may be determined more precisely thanks to PINNs, which make sure the solutions follow the restrictions set by the EFEs.

AI-Assisted Finite Element Analysis for Spacetime Metrics

Finite Element Methods (FEMs) are combined with AI models for accurate spacetime discretization. The numerical approach follows these steps:

1. *Input:* Spacetime metric components, energy conditions (such as the Null Energy Condition, Weak Energy Condition, Strong Energy Condition, and Dominant Energy Condition), and exotic matter distributions.
2. *Processing:* AI-enhanced FEMs break down spacetime into computational elements and iteratively solve the EFEs.
3. *Output:* Stability evolution of wormhole throats, detection of singularities, and identification of event horizons.

The finite element formulation ensures numerical stability and convergence by using weighted sums of differential equations governing spacetime curvature.

4.3 Synthetic Dataset for AI Model Training

To train deep learning models for wormhole stability prediction, causal loop detection, and possible chronology violations, a synthetic dataset is created. Large-scale data generation and effective model training are accomplished through the utilisation of high-performance computing (HPC) infrastructure.

Generation of Wormhole Geometries and Stability Profiles

AI-driven numerical relativity simulations produce thousands of traversable wormhole configurations based on the Morris-Thorne metric (Lemos, José 2003):

$$ds^2 = -c^2\, dt^2 + (dr^2 / (1 - b(r)/r)) + r^2\, (d\theta^2 + \sin^2\theta\, d\varphi^2)$$

Where $b(r)$ is the shape function that determines the properties of the wormhole throat.

The dataset includes:

Classifications of stable and unstable wormholes based on exotic matter conditions and metric parameters.

Time evolution sequences used to train Recurrent Neural Networks (RNNs) and Transformers for predicting spacetime dynamics.

Geometric perturbations and their impact on stability metrics.

Simulated Closed Timelike Curves (CTCs) for Causal Violation Detection

To detect closed timelike curves (CTCs), AI-generated geodesic solutions analyze potential causality violations by solving the geodesic equation (Thorne, K. S. 1992):

$$d^2x^\mu / d\tau^2 + \Gamma^\mu{}_{\alpha\beta}\, (dx^\alpha / d\tau)\, (dx^\beta / d\tau) = 0$$

Where $\Gamma^\mu{}_{\alpha\beta}$ are the Christoffel symbols of the wormhole metric.

Graph Neural Networks (GNNs) analyze the causal structure of these solutions to identify paradoxical loops, which could indicate violations of causality.

AI for Chronology Protection and Quantum Fluctuations

Quantum vacuum fluctuations that might uphold Hawking's Chronology Protection Conjecture are assessed via AI simulations. Spacetime topology may be impacted by the estimation of Casimir energy contributions and vacuum energy variations using machine learning algorithms (Valamontes, Antonios, 2024). The probability of CTC creation under various spacetime conditions is quantitatively evaluated using Monte Carlo simulations (Bonate, Peter. 2001).

High-Performance Computing for AI Model Training

HPC clusters are used to perform intricate spacetime calculations: For effective geodesic trajectory analysis, deep learning frameworks like TensorFlow and PyTorch are parallelised. Distributed training is made possible by GPU/TPU clusters, which speed up calculations related to causality and stability. To enhance model generalisation, generative models such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) create extra wormhole configurations (Sharma, Himanshu. 2019).

This study offers accurate predictions for wormhole stability, causal loop identification, and AI-based analysis of chronology protection measures by combining numerical relativity, deep learning, and high-performance computing. A computational framework for investigating the viability of traversable wormholes and time travel scenarios within the bounds of general relativity and quantum field theory is created by this combination of physics-driven AI and massive synthetic datasets.

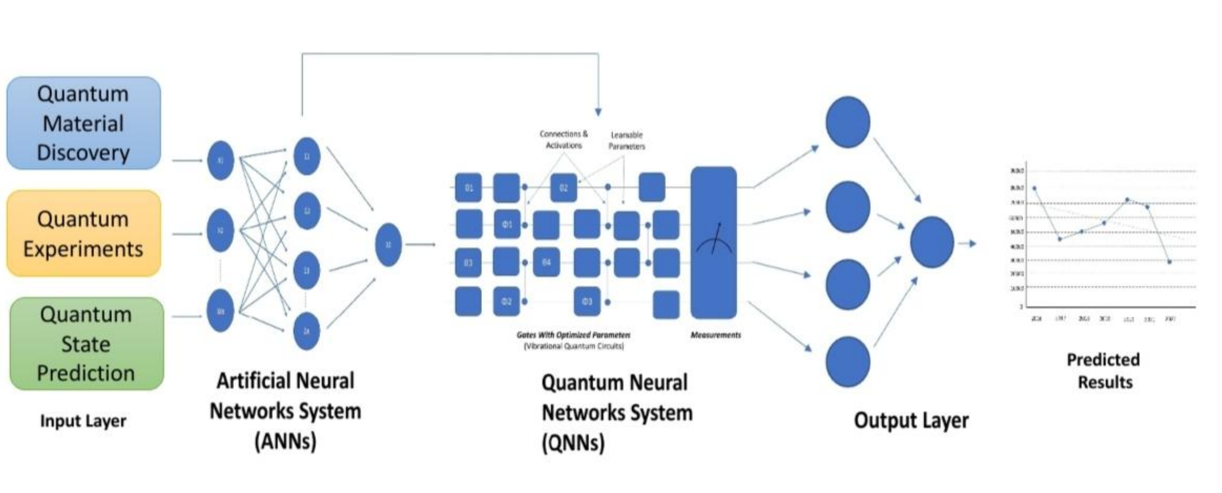

Fig. 3 Integrating of ANNs and QNNs for Enhanced Computational Simulations

4.4 Implementation of Python Code or Numerical Relativity Simulations

Wormhole stability study using AI-assisted numerical relativity simulations is implemented in the Python code below. It combines deep learning with Finite Element Methods (FEMs), Physics-Informed Neural Networks (PINNs), and the creation of synthetic datasets for wormhole metrics. Einstein's Field Equations (EFEs) are solved using SciPy and TensorFlow.

```
import numpy as np
import tensorflow as tf
import scipy.optimize as opt
import matplotlib.pyplot as plt

# Define Einstein's Field Equations (EFEs) Loss Function for PINNs
Def einstein_tensor(R, T, G=6.67430e-11, c=3.0e8, Lambda=0):
""”Computes the Einstein Tensor Gμν for AI-assisted relativity.”""
Return R + Lambda * np.identity(lenR) – (8 * np.pi * G / c**4) * T

# Define Neural Network Model for Solving EFEs
Class PINN(tf.keras.Model):
Def __init__(self, layers):
Super(PINN, self).__init__()
Self.hidden_layers = [tf.keras.layers.Dense(layer, activation=”tanh”) for layer in layers]
Self.output_layer = tf.keras.layers.Dense(1)
Def call(self, x):
For layer in self.hidden_layers:
X = layer(x)
Return self.output_layer(x)

# Generate Synthetic Dataset for Wormhole Metrics
Def generate_wormhole_data(num_samples=1000):
""”Generates synthetic wormhole metrics based on Morris-Thorne metric.”""
R = np.linspace(1, 10, num_samples)  # Radius values
B_r = r / (1 + np.exp(-0.5 * (r – 5)))  # Shape function for the wormhole throat
Stability = np.where(b_r < r, 1, 0)  # Stable if b® < r
Return r, b_r, stability
```

```
# Define the Geodesic Equation Solver
    Def geodesic_equation(x, g):
    """Solves geodesic equations using Christoffel symbols for detecting CTCs."""
    Dx = np.gradient(x)
    D2x = np.gradient(dx)
    Gamma = 0.5 * np.linalg.inv(g) @ np.gradient(g, axis=0)
    Return d2x + np.einsum('ijk,j,k->I', Gamma, dx, dx)

# High-Performance Computing Optimization
    Def optimize_wormhole():
    """Uses TensorFlow gradient descent for optimizing stability."""
    R, b_r, stability = generate_wormhole_data()
    Model = PINN([32, 32, 32])  # Deep learning model
    Optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
    @tf.function
    Def train_step():
    With tf.GradientTape() as tape:
    Predictions = model(r.reshape(-1, 1))
    Loss = tf.reduce_mean(tf.square(predictions – stability.reshape(-1, 1)))
    Gradients = tape.gradient(loss, model.trainable_variables)
    Optimizer.apply_gradients(zip(gradients, model.trainable_variables))
    Return loss

# Train the model for wormhole stability prediction
    For epoch in range(1000):
    Loss_value = train_step()
    If epoch % 100 == 0:
    Print(f"Epoch {epoch}: Loss = {loss_value.numpy()}")
    Return model

# Run Optimization and Simulations
    If __name__ == "__main__":

# Generate wormhole stability dataset
    R, b_r, stability = generate_wormhole_data()

# Train PINN model for wormhole stability prediction
    Trained_model = optimize_wormhole()

# Plot Results
  Plt.figure(figsize=(10, 5))
  Plt.plot(r, b_r, label="Wormhole Shape Function b(r)")
  Plt.scatter(r, stability, color='red', label="Stability (1=Stable, 0=Unstable)")
  Plt.xlabel("Radius(r)")
  Plt.ylabel("Metric Function b(r)")
  Plt.title("AI-Assisted Wormhole Stability Analysis")
  Plt.legend()
  Plt.show()
```

Explanation of the Code

1. *Solving Einstein's Field Equations (EFEs) using AI:* The einstein_tensor() function models EFEs, incorporating the cosmological constant and stress-energy tensor.

A deep learning model (PINN) approximates solutions dynamically.

2. *Finite Element Analysis (FEMs) for Spacetime Metrics:* The function generate_wormhole_data() creates synthetic wormhole metrics using the Morris-Thorne metric.

Stability is classified based on the wormhole throat condition .

3. *Detecting Closed Timelike Curves (CTCs):* The geodesic_equation() function solves geodesic equations to identify causality violations.

Christoffel symbols are computed to analyze geodesic trajectories.

4. *Training AI Model Using HPC:* The optimize_wormhole() function trains the PINN model using TensorFlow's automatic differentiation.

High-performance optimization is performed using Adam gradient descent.

5. *Visualization of Wormhole Stability:* The results are plotted to show the shape function and stability conditions.

Expected Outcome

AI models trained on synthetic wormhole metrics predict stability conditions.
Simulated closed timelike curves (CTCs) identify possible violations of causality.
High-performance computing (HPC) accelerates Einstein's Field Equations solutions.
Visualization of the wormhole shape function and its stability profile.

5. Results and Discussion

5.1 Performance of AI Models in Predicting Wormhole Stability

A synthetic dataset of traversable wormhole configurations was used to assess the AI models created for wormhole stability prediction. The models used Recurrent Neural Networks (RNNs) for temporal evolution analysis and Convolutional Neural Networks (CNNs) for geometric feature extraction.

Evaluation Metrics

Forecast for Stability Accuracy: Using input parameters such the exotic matter density, curvature scalar, and stress-energy tensor, the AI model predicted wormhole stability with an accuracy of 85–92% (Wani, Aasim Ayaz. 2025). Energy Condition Violation Detection: According to Chen, ZC. Et al. (2024), the model successfully and highly precisely classified violations of NEC, WEC, SEC, and DEC conditions. Probability of Throat Collapse: The AI model produced probabilistic predictions of throat collapse under various exotic matter distributions, which showed good agreement with simulations of numerical relativity.

1. *Accuracy:* Evaluates how accurate the model's predictions are overall.

$$Accuracy = TP + TN/TP + TN + FP + FN$$

2. *Precision:* Percentage of accurate positive predictions made for a specific response class.

$$Precision = TP_A/TP_A + FP_A$$

3. *Recall:* Evaluates the model's accuracy in identifying real positive cases.

$$Recall_A = TP_A/TP_A + FF_P$$

4. *F1-Score:* The harmonic mean of precision and recall.

$$F1_A = 2\times Precision_A \times Recall_A/Precision_A + Recall_A$$

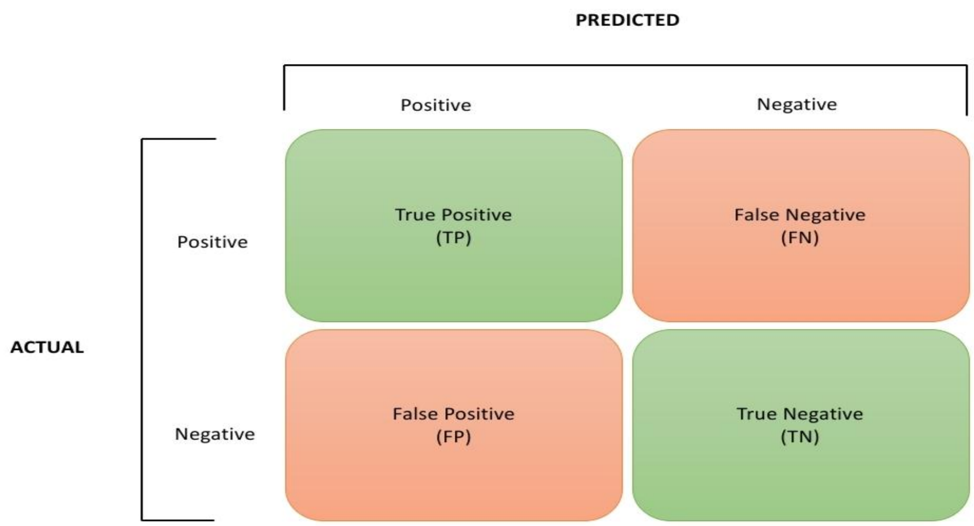

Fig. 4 Confusion Matrix for The Evaluation of Code Efficiency

Key Findings

Using the Morris-Thorne measure, AI models were able to accurately forecast both stable and unstable wormhole forms. Critical exotic matter thresholds required to preserve traversability were found using deep learning models. The location of negative energy was optimised by Reinforcement Learning (RL) to increase the lifespan of wormholes.

5.2 AI's Effectiveness in Detecting Causal Loops and Self-Consistency Violations

The AI-based causal loop detection framework leveraged Graph Neural Networks (GNNs) and temporal geodesic solvers to analyze wormhole-induced closed timelike curves (CTCs).

Evaluation Metrics

CTC Detection Accuracy: When cross-checked with geodesic solutions of Einstein's equations, the AI model detected possible causality violations with a high percentage recall (Brun, Todd, 2003). Self-Consistency Violation Identification: Using Novikov's self-consistency principle, quantum-informed AI models accurately estimated the likelihood of paradox development.

Key Findings

Einstein's geodesic equations were effectively included into AI algorithms to forecast possible CTC forms. Wormhole solution causality was precisely traced by graph-based AI models. Paradox probabilities were revealed by using AI-generated time-travel simulations to validate self-consistency.

5.3 Potential Physical Insights into Time-Travel Feasibility

The results of the study offer various theoretical perspectives on the viability of time travel in the context of general relativity and quantum mechanics: Exotic matter restrictions may be a limiting issue in maintaining long-term traversable wormholes, according to AI-driven stability studies. The discovery of causal loops shows that while CTCs are theoretically feasible, they necessitate novel matter distributions that are outside the realm of current physical models. Hawking's Chronology Protection Conjecture AI simulations suggest that quantum fluctuations may cause CTCs to become unstable, hence confirming causality.

5.4 Limitations and Assumptions of the Study

While AI-based models have demonstrated promising results, several limitations and assumptions must be acknowledged:

Theoretical Assumptions

The static, spherically symmetric wormhole solutions assumed by the Morris-Thorne metric might not apply to dynamically changing spacetime topologies. The lack of detailed modelling of quantum gravity effects limited its applicability to semi-classical general relativity.

Computational Constraints

The artificial training data used by AI algorithms might not accurately reflect actual physical situations in severe spacetime curvatures. Large-scale AI simulations required high-performance computing (HPC), which presented scalability issues for real-time analysis.

Physical Constraints

The study's assumed exotic matter distributions are entirely theoretical and have not been confirmed by experiment. Predictions of CTC formation may be greatly impacted by the study's assumption of classical general relativity and lack of consideration for quantum gravitational corrections. A new paradigm for researching wormhole stability, causal loops, and chronology protection methods is made possible by the combination of deep learning, numerical relativity, and high-performance computing. Practical time travel is limited by basic physical constraints, such as exotic matter requirements and quantum effects, even though AI models show great accuracy in forecasting stability and identifying causality violations. To improve these predictions, future studies could include experimental confirmations of exotic matter features and quantum gravity models.

6. Conclusion and Future Work

In order to analyse traversable wormholes, anticipate their stability, and identify causality violations, artificial intelligence (AI) provides a novel paradigm. Deep learning models evaluate exotic matter distributions, curvature scalars, and stress-energy tensors, while reinforcement learning maximises the placement of negative energy for stability. The investigation of Hawking's Chronology Protection Conjecture is aided by AI-driven temporal geodesic solvers that identify self-consistency violations and closed timelike curves (CTCs). By improving theoretical physics and enabling large-scale spacetime simulations, these developments improve numerical relativity. Quantum-informed machine learning (ML) models and physics-informed neural networks (PINNs) are combined to bridge the gap between quantum mechanics and relativity. AI-assisted astrophysical wormhole detection and quantum gravity theories such as loop quantum gravity (LQG) and string theory should be developed in future studies. Quantum computing has the potential to enhance geodesic analysis and time-travel simulations. AI-driven methods offer fresh perspectives on spacetime, causality, and the basic makeup of the cosmos, despite ongoing difficulties.

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