

Deep learning approach for predicting multiple observables in Au + Au collisions at energies available at the BNL Relativistic Heavy Ion Collider

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We present a data-driven deep learning framework for predicting multiple bulk observables in Au + Au collisions at energies available at the BNL Relativistic Heavy Ion Collider (RHIC). A single neural network is trained exclusively on experimental measurements of charged-particle pseudorapidity density distributions, transverse momentum spectra, and elliptic flow coefficients over a broad range of collision energies and centralities, without using simulation outputs as training targets. The network architecture is inspired by the stages of a heavy-ion collision, from the quark-gluon plasma to chemical and kinetic freeze-out, and employs locally connected hidden layers and a structured input design that encodes basic geometric and kinematic features of the system. We demonstrate that these physics-motivated choices significantly improve test performance compared to purely fully connected baselines. The trained model is then used to predict the above observables at energies available at the RHIC, and the results are further cross-checked against the energy dependence of the total charged-particle multiplicity per participant pair, as well as against a CLVisc hydrodynamic calculation with T_RENT₀ initial conditions. Our findings indicate that such physics-guided neural networks can provide useful data-driven interpolation tools for RHIC observables in regions not currently covered by the available measurements and can support further phenomenological studies.

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I. INTRODUCTION

High-energy heavy-ion collision experiments provide a unique way to explore the properties of matter under extreme conditions. In the experiments, the charged-particle pseudorapidity density distribution ($dN_{\text{ch}}/d\eta$ vs η), transverse momentum dependence of charged particle elliptic flow (v_2 vs p_T), and charged-particle transverse momentum distribution ($dN_{\text{ch}}/2\pi p_T dp_T d\eta$ vs p_T) are important observables for studying the collision processes. These experimental measurements provide important constraints on theoretical and phenomenological descriptions of heavy-ion

collisions, including HIJING [1], EPOS-LHC [2], AMPT [3], PACIAE [4], and relativistic hydrodynamic models [5,6]. Such comparisons help improve our understanding of the properties of the quark-gluon plasma (QGP), final-state particle production, and the underlying particle-production mechanisms.

With advances in GPU hardware and the increasing availability of large datasets, machine learning has developed rapidly in recent years and has been increasingly applied to scientific research including high-energy nuclear physics [7–26]. In Ref. [9], a novel generative adversarial network architecture was applied to the production of jet images. In Ref. [10], a state-of-the-art machine learning method is adopted to study the coordinate and momentum space configurations of the net baryon number in heavy-ion collisions that undergo spinodal decomposition, due to a first-order phase transition. In Ref. [11], a point cloud network with dynamical edge convolution is employed to identify events with critical fluctuations through supervised learning and pick out a large fraction of signal particles used for decision-making in each single event. In Ref. [12], a deep learning feed-forward network is used for estimating elliptic flow coefficients in heavy-ion collisions. In Ref. [13], a deep-learning-based event characterization method is proposed for fast, online event-by-event impact parameter determination at

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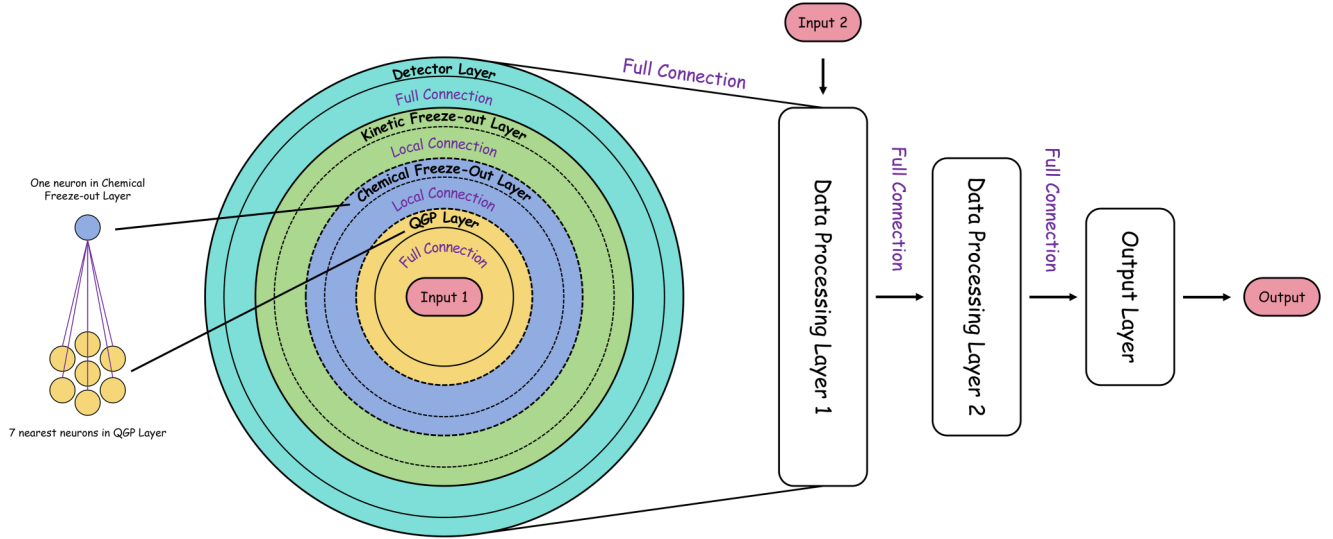


FIG. 1. Schematic illustration of the neural-network model with local connections.

the CBM experiment. These studies demonstrate that machine learning has become a powerful tool for studies in high-energy nuclear physics.

In experiments, abundant experimental data in Au + Au collisions have been measured by collaborations at the BNL Relativistic Heavy Ion Collider (RHIC), e.g., the charged particle pseudorapidity density distributions, the particle transverse momentum distributions, and the transverse momentum dependence of the elliptic flow of particles [27–38]. However, the collision energy points are still very limited due to practical reasons, such as physics goals, cost, and time. In this paper, a neural-network model is built based on the high-energy heavy-ion collision experiment processes to study and predict several experimental observables for which the experimental data are not available. This neural-network model is trained by using the pseudorapidity density distributions, elliptic flow, and transverse momentum distributions of charged particles in Au + Au collisions at the RHIC. The model, which incorporates physical insights into its design, is also compared with alternative approaches and demonstrates better performance. Then the trained neural network is used to make predictions about these observables for unexplored energies. The collision energy $\sqrt{s_{NN}}$ dependence of the total charged-particle multiplicity per participant pair is also used to assess the accuracy of the predictions.

The paper is organized as follows. In Sec. II, we introduce the neural-network model. In Sec. III, we present the comparison of the results from our model and alternative approaches. The training, test results, and predictions of pseudorapidity density distribution, elliptic flow, and transverse momentum distribution of charged particles given by the neural-network model are shown. The verification results of predictions using the total charged-particle multiplicity per participant pair are presented. The dependencies of the predicted total charged-particle multiplicity on the number of participants are also discussed. In Sec. IV, a brief conclusion is drawn.

II. MODEL FRAMEWORK

High-energy heavy-ion collision experiments can be generalized into the following stages. First, two heavy ions colliding at high energy undergo a preequilibrium stage and produce the high-temperature and high-density QGP matter. Second, after evolution, the QGP begins hadronization and reaches chemical freeze-out; i.e., the particle composition is essentially fixed. Third, the particles that have reached chemical freeze-out gradually stop interacting and reach kinetic freeze-out. Fourth, the particles that have reached kinetic freeze-out continue on and eventually reach the detector. Then the data are analyzed and presented as the final experimental results, such as the pseudorapidity density distributions, elliptic flow, and transverse momentum spectra of particles.

A neural-network model is built to mimic the high-energy heavy-ion collision experiment procedures described above (see Fig. 1). The model architecture includes six hidden layers: the QGP layer, the chemical freeze-out layer, the kinetic freeze-out layer, the detector layer, and two data processing layers, as well as two input layers and one output layer, corresponding to the different stages of the experiment. Considering the limited size of the training set and the performance of the neural network, we do not require the network to directly output the full dependence of an observable on the final-particle kinematic variable from the collision-system information alone. Instead, we adopt a dual-input structure. Input 1 contains the initial collision-system information. For example, (196.97, 196.97, 19.6, 0, 10) represents an Au + Au collision system, where 196.97 and 196.97 are the relative atomic masses of the two colliding nuclei, 19.6 is the collision energy in units of GeV, and 0 and 10 denote the lower and upper limits of the centrality bin. Input 2 is introduced at data-processing layer 1. It contains the final-particle kinematic variable together with a one-hot label specifying the observable type. For example, (η , 1, 0, 0) denotes the pseudorapidity variable for the charged-particle pseudorapidity density distribution. With these two inputs, the neural network

TABLE I. The experimental data included in the training and test set.

Observables (Charged)	Collision energy in the training set (GeV)	Collision energy in the test set (GeV)
Pseudorapidity density distributions	19.6, 62.4, 200	130
Elliptic flow	7.7, 9.2, 11.5, 14.5, 27, 62.4, 130, 200	19.6, 39
Transverse momentum distributions	7.7, 11.5, 14.5, 27, 39, 62.4, 200	19.6, 130

outputs the value of the selected observable, such as $dN/d\eta$, at the corresponding kinematic bin. In this setup, each training sample corresponds to a single experimental bin value. The centrality information is encoded in input 1 through the lower and upper limits of the corresponding centrality bin, while input 2 specifies both the final-state kinematic variable and the observable type. No explicit monotonicity or shape constraints are imposed on the output. We assume the evolution from the QGP stage to the kinetic freeze-out stage as a uniformly expanding fireball. Therefore, we distribute the neurons in the QGP, chemical freeze-out, and kinetic freeze-out layers uniformly on the spheres with increasing radius. The method of uniform distribution is the Fibonacci grid,

$$\begin{aligned} z_n &= R \left(\frac{2n-1}{N} - 1 \right), \\ x_n &= \sqrt{R^2 - z_n^2} \cos(2\pi n\phi), \\ y_n &= \sqrt{R^2 - z_n^2} \sin(2\pi n\phi), \end{aligned} \quad (1)$$

where z_n , x_n , and y_n are the coordinates of the n th neuron on the sphere centered at the coordinate origin, R is the radius of the sphere, N is the total number of neurons in the layer, and ϕ is the golden ratio. With this distribution, we can determine the distance between neurons and implement the local connection between the QGP, chemical freeze-out, and kinetic freeze-out layers. Each neuron in the chemical freeze-out layer is connected only to its seven nearest neighbors in the QGP layer, and the same principle is applied to the connection between the chemical freeze-out layer and the kinetic freeze-out layer. The number of nearest neighbors is determined by the local geometry of the Fibonacci-grid representation. For each neuron, we first identify the nearest neuron in the adjacent layer and then include the first surrounding ring around it. In our implementation, this local patch contains seven neighboring neurons. Therefore, the choice of seven nearest neighbors is a geometry-based local-connectivity setting rather than a result of simulation-guided tuning. This structured sparse connectivity suppresses unnecessary long-range couplings while preserving local correlations between adjacent stages of the collision, thereby acting as a physically interpretable form of structural regularization. Full connectivity is retained for all other layer-to-layer connections. The two data-processing layers are fully connected layers after the detector layer. Input 2 is introduced at data-processing layer 1, while data-processing layer 2 further processes the combined representation before the output layer.

The neural-network model is implemented with PyTorch [39]. The model consists of layers with neuron counts of 200,

300, 400, 400, 304, 204, and 1 from the QGP layer to the output layer, respectively. These neuron numbers were chosen empirically through repeated tests of candidate layer sizes, aiming at a reasonable balance between model capacity and generalization performance. Leaky ReLU [40] is used as the activation function for the hidden layers, while no activation function is applied to the output layer. The model is optimized using the ADAM optimizer [41], and Huber loss is used as the loss function,

$$L(y - \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2, & \text{if } |y - \hat{y}| \leq 1, \\ |y - \hat{y}| - \frac{1}{2}, & \text{if } |y - \hat{y}| > 1, \end{cases} \quad (2)$$

where y is the experimental data and $\hat{y}$ is the prediction given by the neural network. The training set includes charged-particle pseudorapidity density distributions in Au + Au collisions at $\sqrt{s_{NN}} = 19.6, 62.4$, and 200 GeV [27,28]; transverse momentum dependence of charged particle elliptic flow in Au + Au collisions at $\sqrt{s_{NN}} = 7.7, 9.2, 11.5, 14.5, 27, 62.4, 130$, and 200 GeV [30–35]; and transverse momentum distribution of charged particles produced in Au + Au collisions at $\sqrt{s_{NN}} = 7.7, 11.5, 14.5, 27, 39, 62.4$, and 200 GeV [36,37]. The test set includes charged-particle pseudorapidity density distributions in Au + Au collisions at $\sqrt{s_{NN}} = 130$ GeV [27], transverse momentum dependence of charged-particle elliptic flow in Au + Au collisions at 19.6 and 39 GeV [30], and transverse momentum distribution of charged particles produced in Au + Au collisions at 19.6 and 130 GeV [36,38]. See Table I for clarity. All three kinds of experimental data are simultaneously used to train and test the neural-network model.

III. RESULTS

In recent studies [12–17], some neural networks have been trained using a combination of experimental data and synthetic data produced by different models, such as hydrodynamic simulations or transport models. This combined approach provides a more diverse set of training data and may improve model generalization. In contrast, our work exclusively uses experimental data to train the neural network. This approach tests the capability of the neural-network model to learn directly from experimental data. In the present work, “exclusively uses experimental data” refers to the training data, whereas the network architecture still incorporates a physics-motivated prior structure. The final hyperparameter configuration was chosen empirically during model development rather than by simulation-guided studies. Here, the generalization behavior refers to the stability of the training and test losses, the absence of evident overfitting, and the

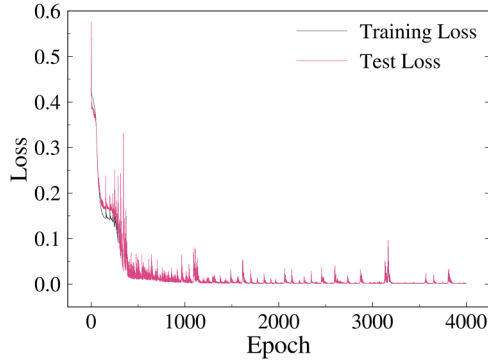


FIG. 2. The training and test loss of the neural-network model as a function of the training epochs.

agreement between the neural-network results and the experimental data at the test energies. Accordingly, the adopted connectivity range should be understood as part of the imposed prior structure rather than as a quantity tuned from simulation data.

Due to the significant differences in value ranges among the three data categories, a direct combination of the raw data could lead to a biased or ineffective training process. Therefore, each observable category was standardized independently using the usual z -score normalization, i.e., subtracting the mean and dividing by the standard deviation, with the mean and standard deviation determined from the training data only, before combining them into a unified dataset. For the transverse momentum distributions of charged particles, a logarithmic transformation was first applied and the standardization was then performed on the transformed values. This preprocessing brings the different observables to comparable numerical scales and helps prevent the training procedure from being biased toward categories with larger absolute magnitudes.

In Fig. 2, the training and test losses of the neural network are shown. It is important to note that without employing local connections, or without splitting the input into two parts and feeding them into the neural network from different locations, such satisfactory results cannot be achieved. For comparison, we also considered a model in which the locally connected layers were replaced by fully connected layers followed by dropout. Dropout is a commonly used regularization method that randomly sets a fraction of neuron activations to 0 during training to reduce overfitting. In this comparison, the dropout rate was chosen to be comparable to the sparsity level of the locally connected architecture. Unlike the fixed local connections, dropout introduces unstructured random sparsity. Even

with this comparable sparsity, the dropout-based model fails to yield comparable performance. The best training and test losses for different models are summarized in Table II, where the test loss is used for a direct comparison of model variants on the same data split. These results demonstrate that incorporating physical insights plays a crucial role in the design of effective neural-network architectures [22].

In Fig. 3, the training results of the neural network (NN) for the charged-particle pseudorapidity density distributions with $\sqrt{s_{NN}} = 19.6, 62.4$, and 200 GeV at different centrality bins in Au + Au collisions are shown. The training results of the neural network are consistent with the experimental data except for the charged-particle data at $|\eta| > 4$ in Au + Au collisions at $\sqrt{s_{NN}} = 19.6$ GeV, which lie in the beam-remnant region where longitudinal fragmentation effects dominate and are not strongly constrained by our training data. We therefore do not expect the present architecture, which focuses on bulk particle production, to capture this region quantitatively.

In Fig. 4, the test results of the neural network for the charged-particle pseudorapidity density distributions with $\sqrt{s_{NN}} = 130$ GeV at different centrality bins in Au + Au collisions are shown. As one can see, the neural network performs well on the test set. This indicates that the neural network has shown reasonable generalization within the studied range. It is also worth noting that in the mid-pseudorapidity region, i.e., $|\eta| < 1.5$, the neural-network results are approximately flat in the midrapidity region, which indicates that the model captures the plateau structure of the charged-particle pseudorapidity density distributions at the mid-pseudorapidity.

In Fig. 5, we show the predictions of the neural network and the results given by the CLVisc model for the pseudorapidity density distributions of charged particles with $\sqrt{s_{NN}} = 17.3, 39$, and 54.4 GeV at different centrality bins in Au + Au collisions. Since the relative experimental uncertainties of the corresponding pseudorapidity-density data are typically of order 10%, we show an additional $\pm 10\%$ reference band around the neural-network predictions as a visual guide. This band is not meant to represent a statistical uncertainty estimate of the neural network itself, but only to indicate a typical experimental uncertainty scale for comparison with the CLVisc results. The CLVisc model parameters are tuned based on the charged-particle pseudorapidity density distributions in the most-central collision. See the Appendix for details. It can be found that the results given by the neural-network and CLVisc models at different centrality bins are basically consistent within the reference band. The comparison with the CLVisc hydrodynamic calculations provides an additional cross-check of the neural-network results,

TABLE II. The best training and test loss for different neural-network models.

Neural-network models	Training loss	Test loss
Model used	1.41×10^{-3}	0.71×10^{-3}
Model without local connection	5.72×10^{-3}	3.77×10^{-3}
Model without splitting the input	3.18×10^{-3}	1.61×10^{-3}
Model without local connection and splitting the input	17.65×10^{-3}	4.88×10^{-3}
Model with local connections replaced by dropout layers	3.35×10^{-3}	1.07×10^{-3}

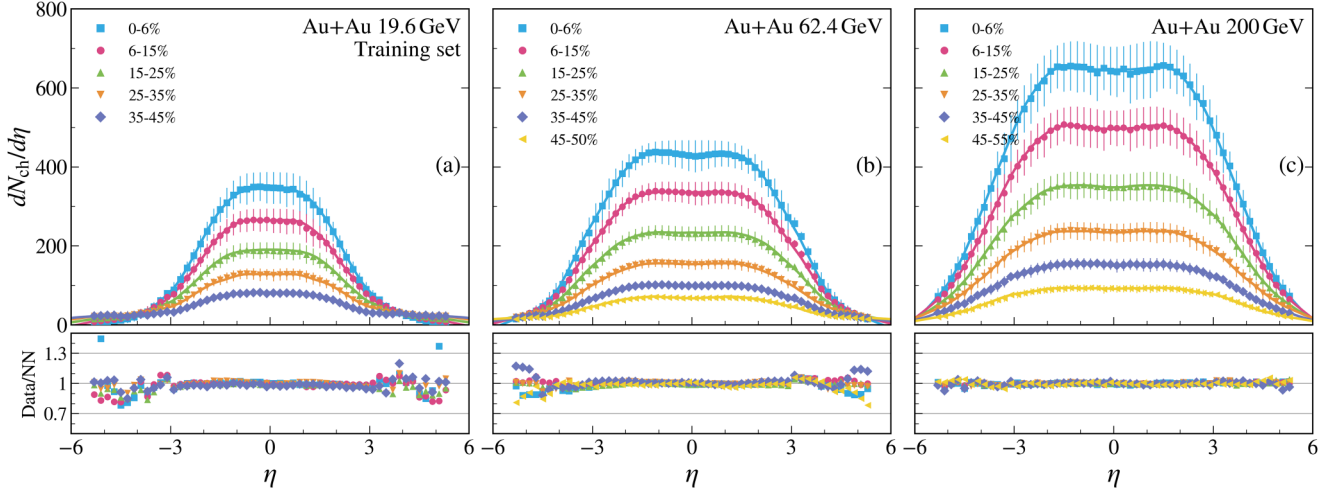


FIG. 3. The charged-particle pseudorapidity density distributions produced in Au + Au collisions at $\sqrt{s_{NN}} = 19.6, 62.4$, and 200 GeV for different centralities. The symbols are experimental data taken from Refs. [27,28]. The curves are the training results of the neural network. The corresponding ratios of data/NN are also shown.

lending support to their physical plausibility within the quoted uncertainties. We note that the neural network can provide reasonable predictions for collision centralities not included in the training set at low collision energies, suggesting a degree of generalization across centrality.

In Fig. 6, we show the total charged-particle multiplicity per participant pair versus the collision energy for the most-central centrality. The full line is the fitting result for all collision energies, excluding neural-network model and CLVisc model results. The total charged-particle multiplicity is obtained from the neural-network prediction of the pseudorapidity density by summing over the η bins (equivalently integrating over the bin widths), and the corresponding

number of participants in Au + Au collisions at $\sqrt{s_{NN}} = 17.3, 39$, and 54.4 GeV is generated by T_RENT₀. One can observe that the predictions of the neural network and the results of the CLVisc model are consistent with the fitting result for all collision energies (solid line), which provides an additional consistency check for the neural-network predictions.

In Fig. 7, we show the total charged-particle multiplicity versus the number of participants. The fitting function from Ref. [47] can reproduce all the predictions of the neural network well. The number of participants is generated by T_RENT₀. We find that the results given by the CLVisc model are slightly lower than those given by the neural-network model, except for the most-central collisions used to tune the parameters of the CLVisc model. It can also be found that the dependence of the total charged-particle multiplicity given by the neural network on the number of participants is similar to that given by the experimental collaborations [49–51], which provides an additional, albeit indirect, consistency check on the neural-network predictions.

In Fig. 8, the training results of the neural network for the transverse momentum dependence of charged-particle elliptic flow with $\sqrt{s_{NN}} = 7.7, 9.2, 11.5, 14.5, 27, 62.4, 130$, and 200 GeV at different centrality bins in Au + Au collisions are shown. It can be seen that the results from the neural network agree well with the experimental data, except for the region where the measured elliptic flow exhibits large fluctuations, i.e., $p_T \approx 2\text{--}3$ GeV at $\sqrt{s_{NN}} = 7.7, 11.5$, and 14.5 GeV, since the results from the neural network are smooth, similar to those in Ref. [52]. In this range, the curves given by the neural network do not pass through these points, but choose an appropriate path, which indicates that the neural network does not overfit the training set of charged-particle elliptic flow.

In Fig. 9, the test results of the neural network for the transverse momentum dependence of charged-particle elliptic flow with $\sqrt{s_{NN}} = 19.6$ and 39 GeV at different centrality bins in Au + Au collisions are shown. As one can see, the neural network reproduces the experimental results well.

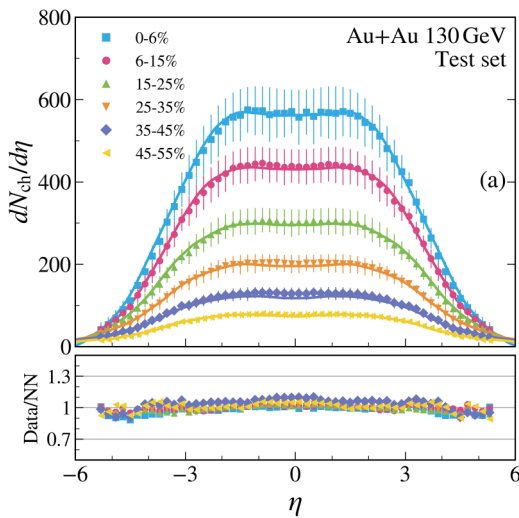


FIG. 4. The charged-particle pseudorapidity density distributions produced in Au + Au collisions at $\sqrt{s_{NN}} = 130$ GeV for different centralities. The symbols are experimental data taken from Ref. [27]. The curves are the test results of the neural network. The corresponding ratios of data/NN are also shown.

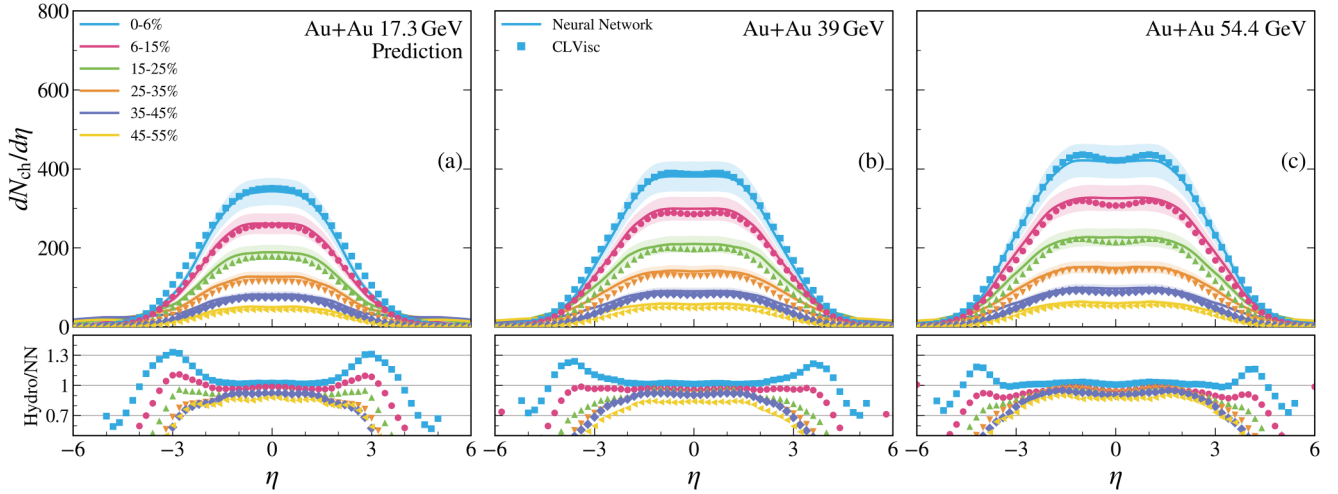


FIG. 5. The charged-particle pseudorapidity density distributions produced in Au + Au collisions at $\sqrt{s_{NN}} = 17.3, 39$, and 54.4 GeV for different centralities. The curves are the predictions of the neural network. The dash-dotted lines are the results of CLVisc. The bands show the $\pm 10\%$ reference range. The corresponding ratios of hydro/NN are also shown.

This indicates that the trained neural network captures the main features of the measured v_2 trends and can provide reasonable interpolative predictions. It is also worth noting that the neural-network results capture the characteristic concave-downward trend of $v_2(p_T)$, namely, its rise at low p_T and its saturation or flattening behavior at intermediate and higher p_T .

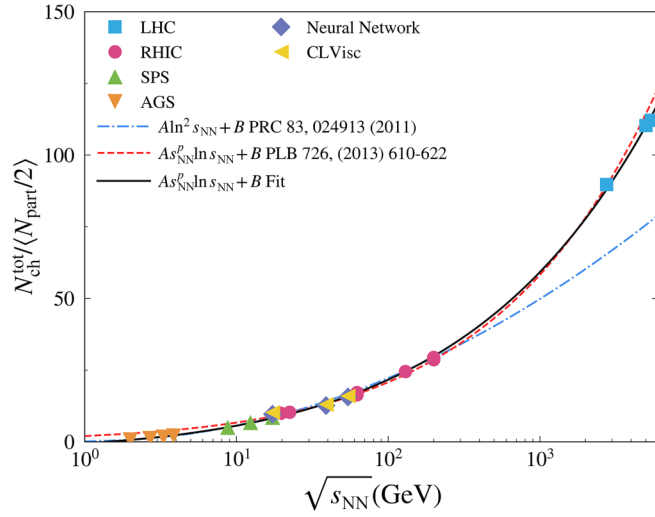


FIG. 6. The total charged-particle multiplicity per participant pair in Au + Au collisions versus $\sqrt{s_{NN}}$ for the most-central centrality. The symbols represent experimental data from BNL Alternating Gradient Synchrotron (AGS) (0–5% Au + Au) [42,43], CERN Super Proton Synchrotron (SPS) (0–5% Pb + Pb) [44,45], RHIC (0–6%, Au + Au and Cu + Cu) [27–29], and CERN Large Hadron Collider (LHC) (0–5%, Pb + Pb and Xe + Xe) [46–48]. The diamonds and left-facing triangles are the results of the neural-network and CLVisc models, respectively. The dashed and dash-dotted lines are the results from fit to lower-energy data [29,46]. The solid line is the result of fit over all experimental data, excluding the results of the neural-network and CLVisc models.

In Fig. 10, we show the predictions of the neural network for the transverse momentum dependence of charged-particle

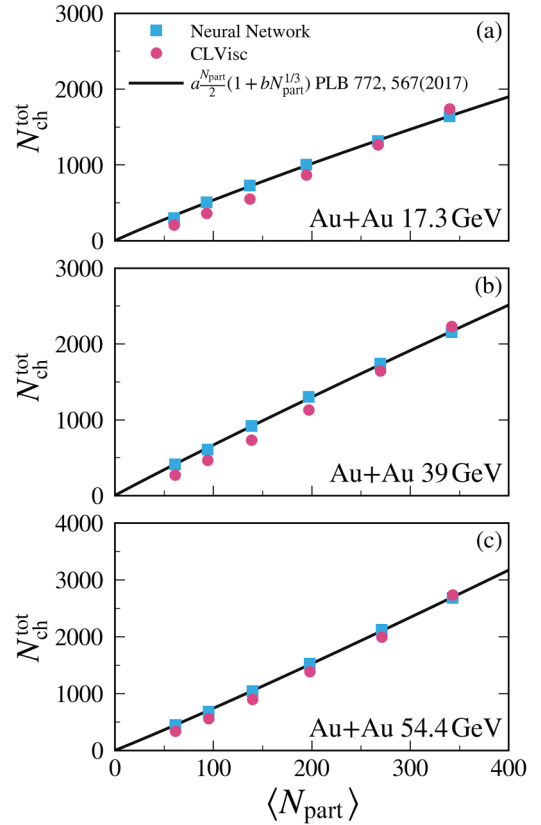


FIG. 7. The total charged-particle multiplicity produced in Au + Au collisions at $\sqrt{s_{NN}} = 17.3, 39$, and 54.4 GeV versus the number of participants. The squares and circles are the results of the neural-network and CLVisc models. The lines are the fitting results for the predictions of the neural network. The fitting function is from Ref. [47].

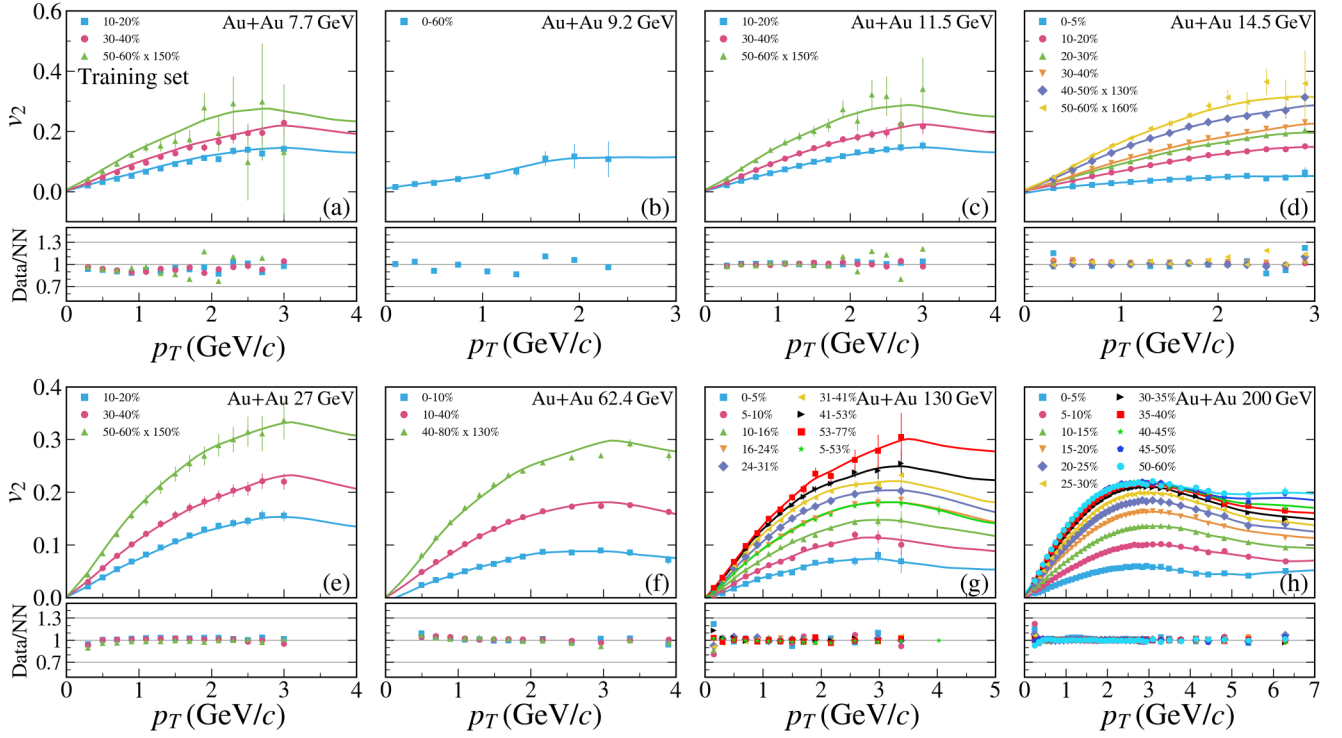


FIG. 8. The transverse momentum dependence of charged-particle elliptic flow in Au + Au collisions at $\sqrt{s_{NN}} = 7.7, 9.2, 11.5, 14.5, 27, 62.4, 130$, and 200 GeV for different centralities. The symbols are experimental data taken from Refs. [30–35]. The curves are the training results of the neural network. The corresponding ratios of data/NN are also shown.

elliptic flow with $\sqrt{s_{NN}} = 13.7, 17.3$, and 54.4 GeV at different centrality bins in Au + Au collisions. Considering the typical experimental uncertainties, a $\pm 10\%$ reference band is also shown around the neural-network predictions as a visual guide. Since the predictions of v_2 given by the neural-network model are smooth curves that vary with p_T , this model may provide a useful interpolative description of elliptic-flow behavior in p_T regions not directly covered by the available measurements.

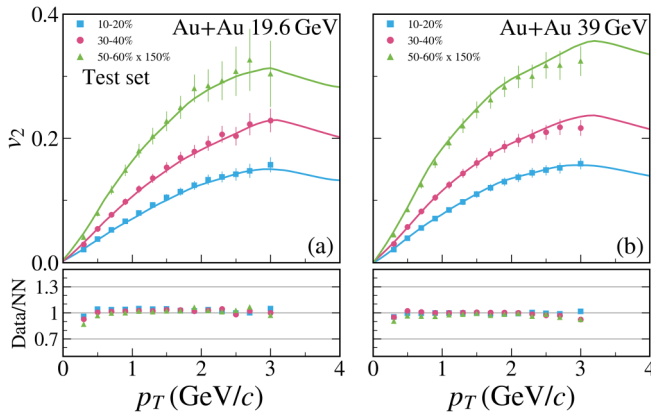


FIG. 9. The transverse momentum dependence of charged-particle elliptic flow in Au + Au collisions at $\sqrt{s_{NN}} = 19.6$ and 39 GeV for different centralities. The symbols are experimental data taken from Ref. [30]. The curves are the test results of the neural network. The corresponding ratios of data/NN are also shown.

In Fig. 11, the training results of the neural network for the transverse momentum distributions of charged particles with $\sqrt{s_{NN}} = 7.7, 11.5, 14.5, 27, 39, 62.4$, and 200 GeV at different centrality bins in Au + Au collisions are shown. It is observed that, using the logarithmic transformation on the experimental data in the training set, the results of the neural network match up well with the experimental data.

In Fig. 12, the test results of the neural network for the transverse momentum distributions of charged particles with $\sqrt{s_{NN}} = 19.6$ and 130 GeV at different centrality bins in Au + Au collisions are shown. As one can see, the neural network describes the experimental data well. This indicates that the trained neural network captures the main features of the measured spectra and can provide reasonable predictions within the studied observable space. It is also worth noting that the neural network captures the characteristic trend wherein particle yield at a given p_T decreases as centrality increases, which indicates its capacity to model essential features of transverse momentum distributions of charged particles across varying collision parameters.

In Fig. 13, we show the predictions of the neural network for the transverse momentum distributions of charged particles with $\sqrt{s_{NN}} = 9.2, 17.3$, and 54.4 GeV at different centrality bins in Au + Au collisions. In view of the experimental uncertainties, a $\pm 10\%$ reference band is also included around the neural-network predictions as a visual guide. These predictions indicate that, by leveraging its training on transverse momentum distributions from a range of collision energies, the neural network is able to capture the main trends of the particle distributions and provide reasonable predictions

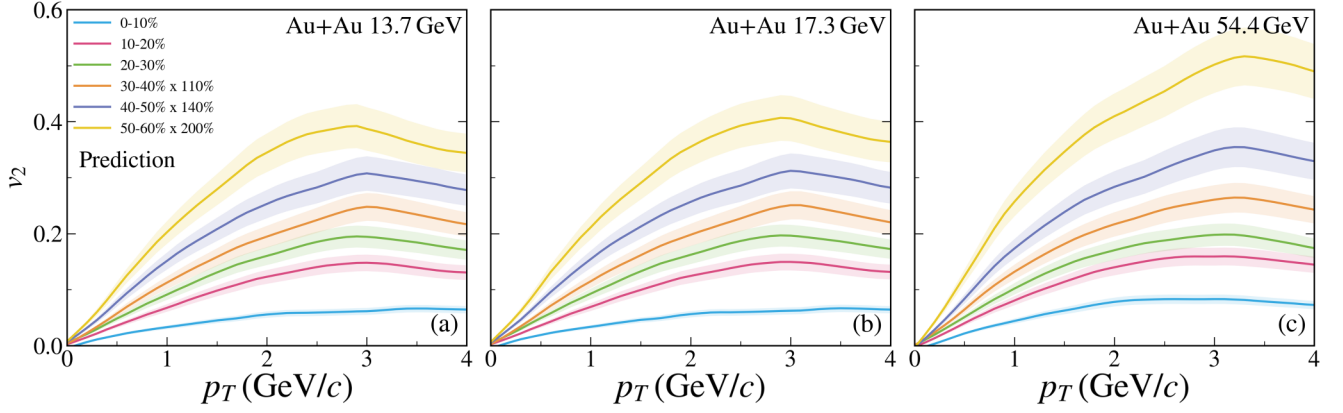


FIG. 10. The transverse momentum dependence of charged-particle elliptic flow in Au + Au collisions at $\sqrt{s_{NN}} = 13.7, 17.3$, and 54.4 GeV for different centralities. The curves are the predictions of the neural network. The bands show the $\pm 10\%$ reference range.

in regions not currently covered by the available measurements.

Overall, it is observed that the neural network can be trained using three kinds of experimental data simultaneously, i.e., pseudorapidity density distributions, transverse-momentum dependence of elliptic flow, and transverse-momentum spectra of charged particles. The model achieves good agreement on both the training and test sets and provides reasonable predictions across all observables. As shown by the ratio panels, the neural-network results generally agree with the available experimental data at the few-to-10% level for most kinematic bins, while larger deviations mainly

appear in regions with stronger experimental fluctuations or limited training data. This provides a quantitative indication of the practical accuracy of the present data-driven approach.

IV. SUMMARY

In this work, we developed a physics-guided deep neural network to predict multiple bulk observables in Au + Au collisions at the RHIC. The architecture is inspired by the space-time stages of a heavy-ion collision and incorporates locally connected hidden layers between QGP, chemical freeze-out, and kinetic freeze-out representations,

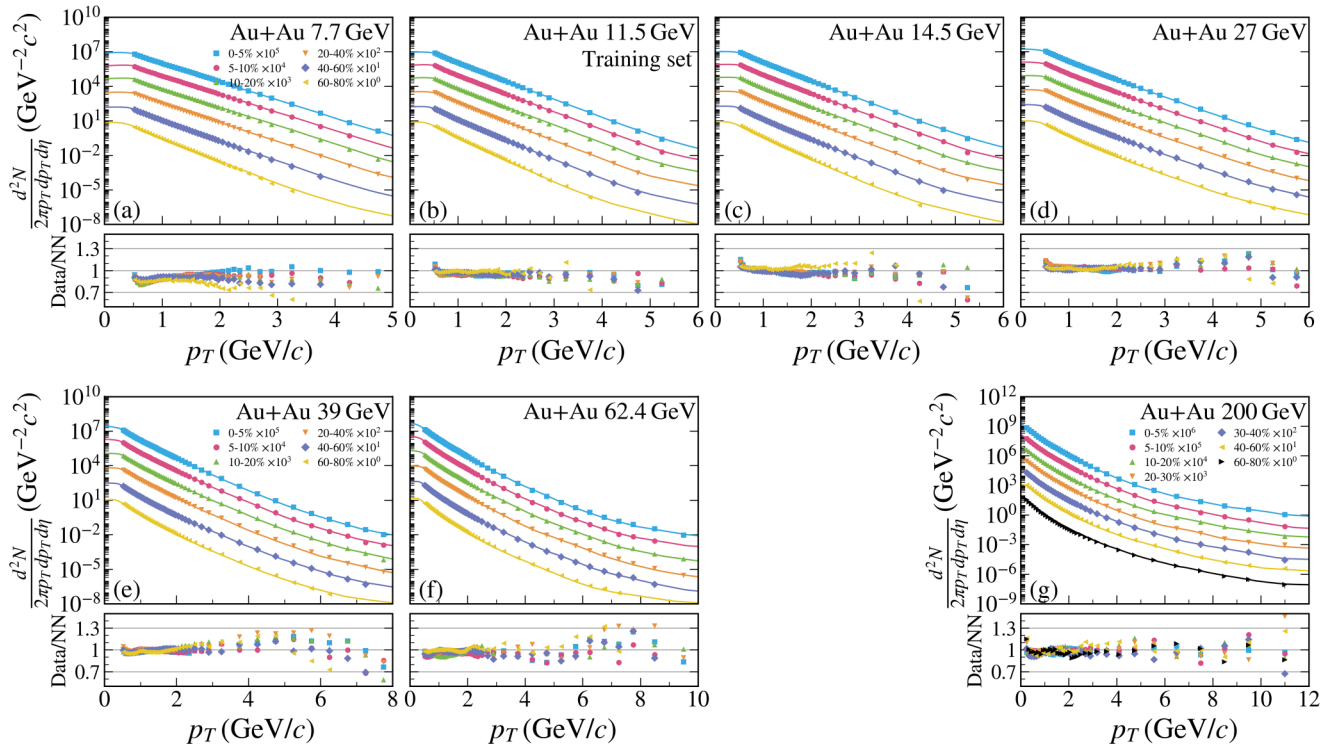


FIG. 11. The transverse momentum distributions of charged particles produced in Au + Au collisions at $\sqrt{s_{NN}} = 7.7, 11.5, 14.5, 27, 39, 62.4$, and 200 GeV for different centralities. The symbols are experimental data taken from Refs. [36,37]. The curves are the training results of the neural network. The corresponding ratios of data/NN are also shown.

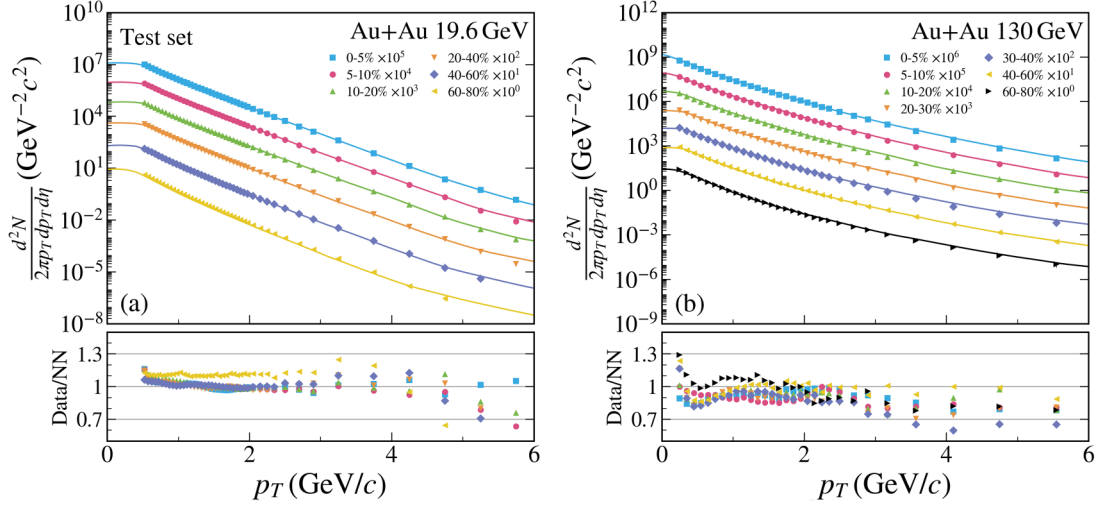


FIG. 12. The transverse momentum distributions of charged particles produced in Au + Au collisions at $\sqrt{s_{NN}} = 19.6$ and 130 GeV for different centralities. The symbols are experimental data taken from Refs. [36,38]. The curves are the test results of the neural network. The corresponding ratios of data/NN are also shown.

together with a structured dual-input design encoding both initial collision characteristics and final-state kinematics. The network is trained exclusively on experimental measurements of charged-particle pseudorapidity density distributions, transverse momentum spectra, and elliptic flow over a broad range of collision energies and centralities, while its architecture incorporates a nontrivial physics-motivated prior structure.

We showed that this architecture can simultaneously reproduce all three classes of observables with low training and test loss and that both local connectivity and input splitting are important for achieving this performance. Comparisons with alternative models further indicate that these physics-guided design elements improve the predictive performance of the network. Using the trained model, we made predictions for charged-particle pseudorapidity density distributions at $\sqrt{s_{NN}} = 17.3$, 39, and 54.4 GeV, charged-particle elliptic flow at $\sqrt{s_{NN}} = 13.7$, 17.3, and 54.4 GeV, and charged-particle transverse momentum distributions at $\sqrt{s_{NN}} = 9.2$, 17.3, and 54.4 GeV in Au + Au collisions, i.e., in regions not currently covered by the available measurements, and

cross-checked the pseudorapidity distribution predictions and the integrated charged-particle multiplicities against a CLVisc hydrodynamic calculation with TRENTo initial conditions and global multiplicity systematics.

Our results show that physics-guided deep learning can provide a useful data-driven tool for multiobservable interpolation and prediction in high-energy nuclear collisions. The present model should be understood as an empirical interpolator in the space of bulk observables and collision parameters: it captures regularities in the available data within an imposed physics-motivated prior structure, but does not constitute a microscopic theory of QCD matter or a parameter-to-observable emulator for direct QGP-property inference. Its predictive success should, therefore, be interpreted cautiously and not by itself as evidence for underlying universality or for a description in terms of only a few effective macroscopic parameters. Future work will aim to extend this framework to additional observables, such as higher-order flow harmonics and identified-particle spectra, to other collision systems, and to incorporate systematic uncertainty estimates via Bayesian or ensemble approaches. With such extensions,

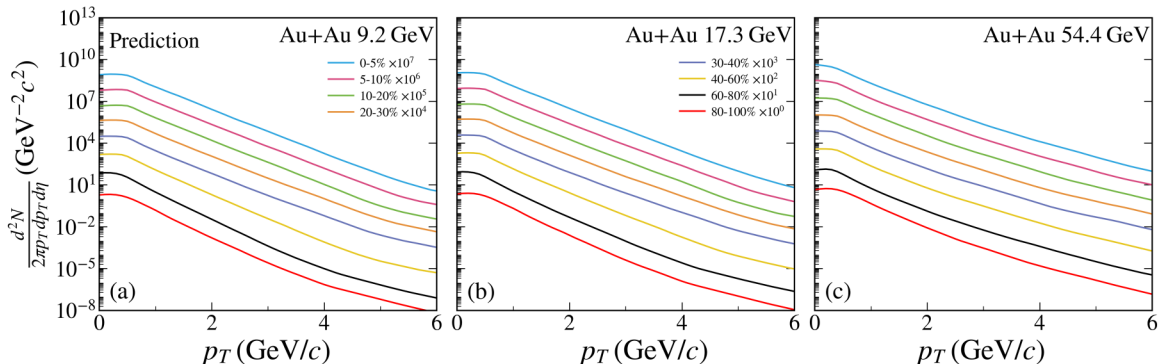


FIG. 13. The transverse momentum distributions of charged particles produced in Au + Au collisions at $\sqrt{s_{NN}} = 9.2$, 17.3, and 54.4 GeV for different centralities. The curves are the predictions of the neural network. The bands show the $\pm 10\%$ reference range.

this type of model may become a useful component in broader phenomenological or inference-oriented workflows.

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DATA AVAILABILITY

The experimental data used for training, testing, and comparison in this work are available from the published sources cited in Refs. [27–38,42–48,59–62]. The additional numerical results generated in this study are available from the corresponding author upon reasonable request.

APPENDIX: CLVisc MODEL WITH T_RENT₀ INITIAL CONDITION

In the following, we briefly introduce the CLVisc model with T_RENT₀. For more details, we refer to Refs. [53–57].

1. Initial condition

T_RENT₀ is a model for the initial conditions of high-energy nuclear collisions and can generate realistic Monte Carlo initial entropy profiles without assuming specific physical mechanisms for entropy production, preequilibrium dynamics, or thermalization. However, T_RENT₀ requires the nucleon-nucleon collision inelastic cross section. In this work, we adopt the parametrization [58]

$$\sigma_{NN}^{\text{inel}} = 17.2031s_{NN}^{0.1641} + 23.8981s_{NN}^{-0.5783}, \quad (\text{A1})$$

where $\sqrt{s_{NN}}$ is the collision energy in units of GeV. This parametrization is shown in Fig. 14, which demonstrates that it can fit the experimental data well. With this fitting result, T_RENT₀ can be used to produce the number of participants at the collision energy that we need. The inelastic cross section used in this paper is already listed in Table III.

In order to describe the charged-particle pseudorapidity density distributions produced in the most-central collision, the initial transverse entropy profile is assumed to be the following form [63],

$$\left. \frac{dS}{dy} \right|_{\tau=\tau_0} = K \cdot T_R, \quad (\text{A2})$$

where τ_0 is the initial proper time for hydrodynamic evolution, K is the scale factor, and T_R is the generalized average of the thickness functions of two nuclei [55]. To describe the plateau

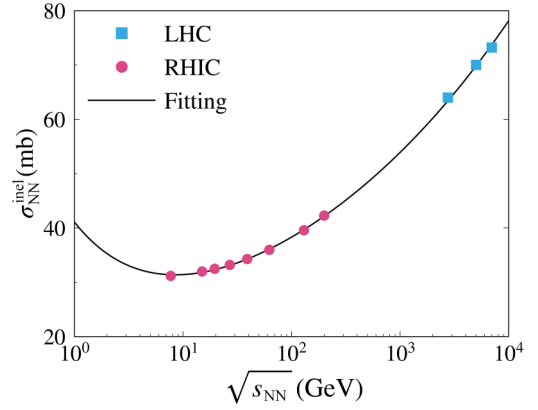


FIG. 14. The NN inelastic collision cross section versus $\sqrt{s_{NN}}$. The circles and squares are the experimental results from the RHIC [59] and the LHC [60–62], respectively. The line is the fitting result from Eq. (A1).

structure in the longitudinal direction, the following function is used [63],

$$H(\eta) = \exp \left[-\frac{(|\eta| - \eta_{\text{flat}})^2}{2\eta_{\text{gw}}^2} \theta(|\eta| - \eta_{\text{flat}}) \right], \quad (\text{A3})$$

where η_{flat} and η_{gw} are parameters. The parameters used for the initial conditions, including τ_0 , K , η_{flat} , and η_{gw} , are tuned to match the charged-particle pseudorapidity density distributions in the most-central collisions. The specific values are listed in Table III.

2. Hydrodynamic evolution

After obtaining the initial condition generated from the T_RENT₀ model, the CLVisc model is used to simulate the hydrodynamic evolution of the collision system through the following energy momentum conservation equation,

$$\nabla_\mu T^{\mu\nu} = 0, \quad (\text{A4})$$

where $T^{\mu\nu}$ is the energy-momentum tensor which is defined as follows,

$$T^{\mu\nu} = \varepsilon u^\mu u^\nu - p \Delta^{\mu\nu} + \pi^{\mu\nu}, \quad (\text{A5})$$

where ε is the energy density, u^μ is the fluid four-velocity, p is the pressure, $\Delta^{\mu\nu} = g^{\mu\nu} - u^\mu u^\nu$ is the projection operator, and $\pi^{\mu\nu}$ is the shear viscosity tensor. $\pi^{\mu\nu}$ is defined based on an Israel-Stewart-like second-order hydrodynamic

TABLE III. The parameters of the initial condition used for Au + Au collisions at different collision energies.

Parameters	54.4 GeV	39 GeV	17.3 GeV
$\sigma_{NN}^{\text{inel}}$ (fm ²)	3.55	3.43	3.21
τ_0 (fm)	0.6	0.6	0.6
K	45	42	40
η_{flat}	2.5	2.2	1.8
η_{gw}	0.1	0.07	0.04

expansion [56],

$$\Delta_{\alpha\beta}^{\mu\nu} u^\sigma \partial_\sigma \pi^{\alpha\beta} = -\frac{1}{\tau_\pi} (\pi^{\mu\nu} - \eta_v \sigma^{\mu\nu}) - \frac{4}{3} \pi^{\mu\nu} \theta - \frac{5}{7} \pi^{\alpha(\mu} \sigma_{\alpha}^{\nu)} + \frac{9}{70} \frac{4}{e+P} \pi_{\alpha}^{(\mu} \pi^{\nu)\alpha}, \quad (\text{A6})$$

where $\Delta_{\alpha\beta}^{\mu\nu} = \frac{1}{2}(\Delta_{\alpha}^{\mu} \Delta_{\beta}^{\nu} + \Delta_{\alpha}^{\nu} \Delta_{\beta}^{\mu}) - \frac{1}{3} \Delta^{\mu\nu} \Delta_{\alpha\beta}$ is second-order symmetric projection operator, τ_π is the relaxation time, η_v is the shear viscosity coefficient, $\theta = \partial_\mu u^\mu$ is the expansion rate, and $\pi^{(\mu\nu)} = \Delta_{\alpha\beta}^{\mu\nu} \pi^{\alpha\beta}$ is the traceless symmetric tensor. The relaxation time τ_π and the shear viscosity coefficient η_v have the following relation with the specific shear viscosity C_{η_v} , which is treated as a model

parameter [56],

$$\tau_\pi = \frac{5C_{\eta_v}}{T}, \quad (\text{A7})$$

$$C_{\eta_v} = \frac{\eta_v T}{e+P}. \quad (\text{A8})$$

The specific shear viscosity C_{η_v} adopted in this paper is 0.08.

In this work, the bulk pressure and the baryon current were not considered. The equation of state used is from the HotQCD Collaboration [64]. When the energy density of the evolving system is lower than the freeze-out energy density ($e_{\text{fz}} = 0.4 \text{ GeV/fm}^3$) [56], the Cooper-Frye formalism [56] is used to obtain the hadron momentum distribution. The resonance decays have been considered. The centrality classes are divided based on the total entropy generated by TrENT_0 .

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