6 (1) September 2023 481-494 ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
JSIKTI: *Jurnal Sistem Informasi dan Komputer terapan Indonesia*

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Research article

Hypertension Risk Prediction Using GRU-Based Deep Learning Optimized with Stochastic Gradient Descent

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ARTICLE INFO

Article history:
Received 1 June 2023
Revised 28 July 2023
Accepted 29 August 2023
Available online 30 September 2023

Keywords:
Hypertension Prediction, GRU Neural Network, Stochastic Gradient Descent, Lifestyle Risk Factors, Deep Learning, Health Data Analytics, Classification Model.

Please cite this article in IEEE style as:
I. D. A. S. Murdhani and I. G. A. A. R. Kerlania, "Hypertension Risk Prediction Using GRU-Based Deep Learning Optimized with Stochastic Gradient Descent," JSIKTI: Jurnal Sistem Informasi dan Komputer Terapan Indonesia, vol. 6, no. 1, pp. 481-494, 2023.

ABSTRACT

Hypertension stands out as a highly common heart disease across the globe, where spotting risks early is vital to curb its prolonged effects. Still, standard check-up approaches usually hinge on unchanging health stats that overlook habit-based risk trends entirely. This gap complicates building precise alert systems for folks with different routines and body profiles. Fueled by the push for a more flexible and trend-focused strategy, the study delves into applying a Gated Recurrent Unit (GRU)-driven neural network to predict hypertension threats using lifestyle and past health data. The model blends sequential trend analysis with two GRU layers, dropout for stability, and L2 limits, tuned via Stochastic Gradient Descent (SGD) with momentum and Nesterov boosts. It lets the network uncover intricate links between factors such as age, salt consumption, stress, BMI, sleep time, family background, and treatment history. Trials on 1,985 patient records reveal solid prediction skills, with top classification rates and well-defined categories in the confusion matrix. The training and validation plots also prove smooth learning without major overfit. Next steps cover enlarging the data with continuous health metrics, incorporating attention tools for clearer insights, and pitting it against cutting-edge optimizers like AdamW and Ranger to enhance broader applicability.

1. Introduction

Hypertension persists as a paramount global health challenge in the current era, with its incidence steadily climbing owing to shifts in daily habits, an older demographic makeup, and external pressures from the surroundings [1]. Serving as a primary driver behind heart-related ailments like cardiac insufficiency and cerebrovascular incidents, it accounts for countless fatalities annually and remains a top source of illness across varied population segments [2]. Numerous investigations highlight that pinpointing hypertension risks at an early stage is pivotal for averting issues, facilitating prompt adjustments in routines and therapeutic measures [3]. Cutting-edge innovations in machine learning and deep learning have broadened the scope for forecasting in medical fields, especially in uncovering nuanced trends within bodily and behavioral information that conventional statistical approaches might miss [4]. Amid the surge in accessible electronic health logs and routine data, computational frameworks adept at handling intricate connections between risk elements have emerged as indispensable in contemporary health data analysis. As a result, explorations into AI-powered hypertension forecasting have surged lately, fostering more flexible and individualized risk evaluation methods [5].

Notwithstanding notable strides, numerous current hypertension forecasting systems grapple with inherent drawbacks. Approaches rooted in classic supervised learning frequently view patient

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
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attributes as isolated entities, disregarding chronological overlaps and intricate, non-straightforward ties among lifestyle aspects including rest periods, tension levels, sodium consumption, drug administration, and ancestral predispositions [6]. Such interconnections are vital in shaping the physiological reactions that fuel hypertension, rendering fixed and straightforward models inadequate for precise categorization [7]. Moreover, health-related data collections are often diverse, cluttered, and skewed, introducing extra hurdles for standard machine learning techniques in forming resilient data depictions [8]. This investigation seeks to tackle these issues by crafting a more versatile and sequence-conscious forecasting tool that can grasp elaborate interrelations within the data. The impetus for this work arises from the necessity to connect lifestyle-oriented risk evaluations with top-tier deep learning frameworks. Given that lifestyle variables are typically interwoven and fluctuating, a system capable of deciphering underlying patterns systematically is key to yielding dependable forecasts. With hypertension threats escalating globally, crafting precise, streamlined, and broadly applicable predictive tools has risen to the forefront for community health and clinical guidance platforms [9].

To surmount the outlined obstacles, this research introduces a deep learning setup centered on Gated Recurrent Units (GRUs) refined via Stochastic Gradient Descent (SGD) for anticipating hypertension based on routine and clinical background details. GRU networks, functioning as an evolution of Recurrent Neural Networks (RNNs), excel in tracking extended dependencies while upholding computational thriftiness, positioning them ideally for organized tabular data harboring concealed variable linkages [10]. Employing a pair of layered GRU components empowers the model to extract multi-tiered interpretations of input data, whereas dropout and L2 regularization counteract excessive fitting and bolster overall adaptability. SGD augmented with momentum and Nesterov acceleration directs the refinement process, promoting steady and swift alignment amid erratic gradient flows [11]. The key advancements from this study encompass: (1) formulating a profound sequential design rooted in GRU customized for habit-influenced hypertension sorting, (2) embedding a sturdy refinement tactic through momentum-enhanced SGD to stabilize alignment, (3) delivering an in-depth assessment of model efficacy via precision metrics, confusion matrix, and progression graphs, and (4) illustrating that GRU-SGD delivers superior forecasting prowess relative to conventional non-sequential alternatives. The framework herein not only scrutinizes unchanging health traits but also uncovers latent correlations between factors that markedly affect hypertension results [12].

Assessing the suggested GRU-SGD framework with a compilation of 1,985 patient entries yields exceptionally encouraging outcomes, where the confusion matrix showcases clear category distinctions and minimal erroneous assignments. Accuracy trajectories for training and verification demonstrate consistent advancement devoid of notable over-adaptation, underscoring the model's prowess in extrapolating to novel data. These observations affirm that profound recurrent architectures, traditionally tied to time-ordered series, can adeptly seize significant associations in structured lifestyle datasets when equipped with fitting stabilization and refinement strategies [13]. The outcomes further bolster the case for utilizing deep learning in habit-grounded health prognostication, offering immense promise for clinical choices and prompt ailment identification. This endeavor ultimately advances the evolution of smart health data processing by validating the practicality and potency of GRU-centric designs for hypertension risk delineation. Subsequent investigations could refine this paradigm by incorporating more comprehensive chronological health documentation, investigating transparent attention tools, and adopting contemporary refiners to further polish alignment behaviors. In essence, the insights herein underscore the value of sophisticated deep learning in tackling multifaceted health forecasting dilemmas and forging more accurate preventive medical tactics [14]. Expanding on the global implications, hypertension's toll extends beyond immediate health crises, influencing economic burdens through lost productivity and healthcare expenditures. For instance, in developing nations, where access to routine screenings is limited, predictive models like the one proposed could democratize early detection, potentially saving lives by integrating with mobile health apps. The GRU architecture's efficiency in handling sequential data also opens doors to real-time monitoring, where wearable devices feed continuous inputs, allowing for dynamic risk reassessments. Furthermore, the emphasis on lifestyle factors aligns with holistic health paradigms, encouraging interdisciplinary collaborations between data scientists and clinicians to refine feature engineering. By addressing data imbalances through techniques like oversampling minority classes, the model could enhance fairness across demographics, reducing disparities in hypertension outcomes. In terms of ethical considerations, ensuring data privacy via anonymization protocols is paramount, as mishandled health records could lead to unintended biases. The study's focus on SGD with momentum not only accelerates learning but also minimizes computational costs, making it feasible for resource-constrained settings. Overall, this work exemplifies how AI can transform preventive care, bridging the gap between technological innovation and equitable health solutions, while paving the way for broader applications in chronic disease management. As societies grapple with aging populations, such adaptive models will be instrumental in curbing the rising tide of cardiovascular threats, fostering a healthier future for generations to come. The integration of deep learning in this context also highlights the need for continuous model updates to account for evolving lifestyle trends, such as increased screen time or dietary shifts, ensuring long-term relevance. Moreover, comparative analyses with other recurrent variants, like LSTMs, could reveal nuanced advantages, enriching the field of health informatics. Ultimately, by prioritizing interpretability through future attention mechanisms, these models can gain clinician trust, facilitating widespread adoption in clinical workflows and policy-making arenas. This holistic approach not only mitigates hypertension's global impact but also sets a precedent for AI-driven interventions in other prevalent conditions, such as diabetes or obesity, where lifestyle interplay is equally critical. The journey toward personalized medicine thus gains momentum, with GRU-based systems at the forefront, promising a paradigm shift in how we perceive and combat chronic illnesses on a worldwide scale. In delving deeper into the model's architecture, the two stacked GRU layers operate synergistically to process inputs layer by layer, each building upon the previous to capture hierarchical patterns. For example, the first layer might focus on basic correlations between age and BMI, while the second delves into more complex interactions involving stress and family history. Dropout, applied at a rate that balances retention of information with noise reduction, prevents the model from memorizing spurious patterns, a common pitfall in healthcare data. L2 regularization, by penalizing large weights, encourages simpler models that generalize better, akin to Occam's razor in machine learning. The choice of SGD with momentum simulates a ball rolling downhill, gaining speed to escape local minima, while Nesterov acceleration anticipates future gradients for smoother trajectories. This optimization suite is particularly adept for the noisy, high-dimensional datasets typical in health studies, where traditional optimizers might oscillate or converge prematurely. The contributions outlined not only advance technical prowess but also address practical needs, such as scalability for large patient cohorts. By demonstrating superior performance over non-sequential baselines, the study validates the shift toward dynamic modeling, where temporal aspects—though not explicitly time-series—are inferred from feature dependencies. This adaptability could extend to other domains, like mental health predictions, where behavioral sequences play a role. Ethically, the model's design promotes transparency by avoiding black-box complexities, allowing for audits that ensure fairness and reduce algorithmic bias. As healthcare embraces AI, frameworks like this will be crucial in navigating the ethical landscape, balancing innovation with accountability. The evaluation metrics, beyond accuracy, include precision and recall, providing a nuanced view of performance in imbalanced classes, where false negatives in hypertension detection could have dire consequences. Training curves, analyzed for plateauing, indicate optimal epoch selection, preventing wasted resources. Validation on unseen data further assures robustness, mitigating overfitting through early stopping techniques. These rigorous assessments position the model as a benchmark for future hypertension studies, encouraging replication and refinement. In conclusion, the GRU-SGD approach not only excels in prediction but also embodies the synergy between deep learning and clinical insights, heralding a new era of intelligent, responsive healthcare systems. Looking ahead, the potential for dataset expansion with time-series elements, such as longitudinal blood pressure readings, could elevate the model's temporal awareness, transforming it into a proactive tool for continuous risk monitoring. Attention mechanisms, by highlighting influential features, would enhance interpretability, enabling clinicians to understand why a prediction was made—crucial for trust and regulatory compliance. Comparisons with AdamW and Ranger optimizers might reveal

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trade-offs in convergence speed versus stability, informing hybrid strategies. Broader implications include integration with electronic health records for seamless deployment, potentially reducing diagnostic delays. The study's findings also advocate for policy changes, such as incentivizing data sharing among institutions to build larger, more diverse datasets. In educational contexts, this work could inspire curricula blending AI with medicine, fostering the next generation of health innovators. Economically, by averting complications, such models could yield cost savings, redirecting funds to preventive programs. Culturally, addressing hypertension in varied demographics requires culturally sensitive features, like incorporating regional dietary habits, to avoid one-size-fits-all pitfalls. The resilience of GRU-SGD in noisy environments underscores its suitability for real-world applications, where data imperfections are the norm. Ultimately, this research not only advances hypertension prediction but also catalyzes a broader AI revolution in healthcare, where predictive power meets ethical responsibility, ensuring that technological progress benefits all strata of society. As we stand on the brink of personalized medicine, models like this illuminate the path forward, transforming challenges into opportunities for healthier, more equitable futures. The emphasis on sequential learning also opens avenues for interdisciplinary research, merging neuroscience insights on memory with computational modeling. By quantifying the impact of lifestyle interventions, the framework could inform public health campaigns, quantifying benefits like reduced salt intake. In summary, the GRU-SGD model's success is a testament to the transformative potential of deep learning, urging continued investment in AI for sustainable health advancements.

2. Related Work

Investigations into forecasting hypertension through lifestyle and medical elements have surged dramatically lately, fueled by the escalating access to electronic health documentation. A plethora of research underscores the robust link between hypertension and behavioral elements like sodium consumption, rest hours, anxiety intensity, body mass index (BMI), hereditary background, and compliance with prescribed drugs. Initial efforts in categorizing hypertension via lifestyle inputs revealed these components as key influencers on systolic and diastolic pressures; yet, conventional statistical frameworks frequently falter in grasping the elaborate, non-linear synergies between them [15]. The data collection applied here features a blend of quantitative and coded qualitative attributes—encompassing BP_History, Medication, Exercise_Level, and Smoking_Status—underscoring the demand for advanced methods to navigate the complex ties within the information.

Conventional machine learning tactics, such as logistic regression, Support Vector Machines (SVM), and decision trees, are commonly deployed for hypertension forecasting owing to their straightforwardness and clarity. However, these established techniques generally presume linear divisibility or unrelated feature connections, which might not sufficiently represent the multifaceted nature of hypertension vulnerability [16]. Past investigations noted hurdles in extending their frameworks to wider audiences, largely stemming from dependence on manual feature crafting and failure to detect concealed linkages between variables. For collections like the one in this analysis—encompassing 1,985 instances with coded qualitative traits and diverse quantitative ranges—these constraints become particularly evident, stressing the requirement for systems that autonomously and adeptly derive hidden depictions.

Lately, deep learning has emerged as a cornerstone in clinical risk estimation, providing unmatched versatility in simulating non-linear and multi-dimensional information. Multilayer Perceptron (MLP) systems have been utilized to anticipate hypertension and heart-related dangers, and while they often surpass traditional methods, they are limited by their forward-only design, which fails to naturally account for inter-feature correlations [17]. This drawback has spurred experts to investigate sequential frameworks like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU). Though originally crafted for temporal sequences, these recurrent designs have proven exceptionally potent on organized tabular data where variable relations display contextual or progressive traits. For instance, anxiety levels could affect rest periods, which in turn influence BMI, illustrating an implicit sequence of impacts that forward-only models miss.

Various comparison analyses spotlight the benefits of GRU compared to LSTM in medical forecasting tasks. GRU architectures utilize fewer components and streamlined gating processes while preserving the capacity to handle extended dependencies, facilitating quicker stabilization and

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lowering overfitting risks—a vital factor with moderately sized datasets as in this inquiry [18]. This productivity positions GRU as an ideal option for habit-based hypertension estimation, particularly after inputs are refined through standardization and qualitative coding. The examined collection includes elements like Age, Salt Intake, Stress Score, Sleep Duration, BMI, Family History, and Smoking Status, all conducive to GRU modeling given their interwoven behavioral dynamics.

Refinement strategies are equally pivotal in shaping deep learning efficacy. Although adaptive optimizers like Adam and RMSprop are prevalent for their flexible learning traits, increasing evidence suggests that Stochastic Gradient Descent (SGD) enhanced with momentum and Nesterov acceleration frequently delivers superior adaptability in specific scenarios [19]. Particularly in frameworks with stabilization tools such as dropout and L2 penalties, SGD tends to align more steadily and sidestep the abrupt lows linked to excessive adaptation. This insight matches the outcomes here, with learning and testing precision graphs showing steady gains and consistent alignment over 1000 iterations, evidencing robust refinement backed by a 0.3 dropout ratio and L2(1e-4) constraints across layer.

Further explorations stress the value of confusion matrix scrutiny in affirming medical categorization model results. Investigations on persistent ailment estimation—including hypertension, diabetes, and heart risks—indicate that deep learning systems achieve heightened sensitivity and precision versus traditional algorithms when adequately trained and stabilized [20]. The confusion matrix from this work mirrors this pattern: elevated correct positive and negative tallies with scant errors. Precisely, the system accurately pinpointed 52 non-hypertensive and 59 hypertensive cases, with few wrong calls, showcasing solid category differentiation and minimal favoritism toward any group.

Contemporary publications from 2021 to 2025 also accentuate the integration of behavioral and genetic aspects into forecasting structures. For example, research blending anxiety metrics, rest spans, physical engagement, and familial records regularly achieves boosted accuracy over models focused only on bodily readings [21]. The data here corresponds with these discoveries, featuring exhaustive behavioral attributes vital for a sturdy hypertension model. This further endorses the GRU choice, as its progressive capabilities extract refined connections from coded variables, amplifying the model's foresight.

Additionally, extensive studies on RNN frameworks for metabolic and cardiac ailment estimation offer compelling support for GRU in behavioral datasets. Work in diabetes anticipation, weight categorization, and heart failure prognosis shows GRU networks excel in seizing bodily and behavioral motifs beyond MLP and other forward networks [22]. These results bolster the notion that GRU suits non-chronological yet mutually dependent feature groups like those here.

Data preparation methods are extensively debated in existing literature, stressing the need for qualitative variable coding, quantitative feature scaling, and uniform normalization throughout collections. Such practices greatly affect deep learning outcomes by establishing a consistent input domain that secures training and curbs noise vulnerability [23]. The collection in this study adheres strictly to these advised preparation stages—converting variables to numeric codes and maintaining uniform structure across all traits—thus boosting synergy with GRU designs and ensuring dependable model alignment.

In summary, the amassed prior research reveals a distinct shift toward deep learning for hypertension forecasting, with a focus on detecting non-linear and codependent behavioral motifs. The GRU–SGD framework here resonates with these contemporary trends, presenting a design that's not just computationally savvy but also adept at uncovering hidden ties in health variables. The assessment indicators from this work—encompassing categorization precision, confusion matrix efficacy, and steady decline graphs—further affirm the method's potency. Therefore, this analysis extends and enriches the literature by proving that a GRU-driven progressive framework, paired with momentum-guided SGD refinement and fitting stabilization tactics, can attain trustworthy and adaptable hypertension estimation rooted in behavioral and clinical histories.

Expanding on the dataset's intricacies, the 1,985 samples offer a rich tapestry of patient profiles, each encoded with variables that reflect real-world variability. For instance, BP_History captures past blood pressure trends, while Medication tracks adherence patterns, revealing how inconsistent drug use might exacerbate risks. Exercise_Level and Smoking_Status add layers of behavioral nuance,

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showing how sedentary lifestyles or tobacco habits intertwine with stress to elevate hypertension probabilities. This diversity necessitates preprocessing that goes beyond basic encoding; techniques like one-hot transformation for categoricals ensure no information is lost, while min-max scaling for numericals prevents dominance by outliers. Such meticulous handling not only prepares the data for GRU ingestion but also mirrors best practices in health informatics, where data integrity directly correlates with model reliability. Moreover, the absence of temporal sequences in the dataset doesn't diminish GRU's utility; instead, it highlights the model's ability to infer pseudo-sequential relationships, treating features as interdependent nodes in a behavioral network. This approach aligns with emerging paradigms in personalized medicine, where static snapshots of lifestyle yield dynamic insights into chronic disease trajectories.

Delving into GRU's architectural strengths, the gating mechanisms—update and reset gates—allow selective memory retention, crucial for filtering relevant lifestyle signals amidst noise. Unlike LSTMs, which juggle three gates, GRU's simplicity reduces computational overhead, making it ideal for resource-limited clinical settings. In this study, stacking two GRU layers builds hierarchical feature representations: the first layer aggregates basic interactions, like age and BMI correlations, while the second refines complex dependencies, such as how stress modulates sleep and, consequently, medication efficacy. Dropout at 0.3 randomly deactivates neurons during training, simulating ensemble learning and preventing co-adaptation, while L2 regularization curbs weight explosion, promoting parsimonious models that generalize across unseen patient cohorts. This combination not only mitigates overfitting but also enhances interpretability, as stabilized weights can be analyzed for feature importance, aiding clinicians in decision-making.

Optimization with SGD, augmented by momentum and Nesterov acceleration, introduces a physics-inspired dynamism: momentum accumulates past gradients to build velocity, propelling the model out of shallow minima, while Nesterov peeks ahead to adjust direction preemptively. This results in smoother convergence, as evidenced by the 1000-epoch curves showing monotonic accuracy rise without erratic spikes. Compared to adaptive optimizers, SGD's fixed learning rate fosters robustness in noisy health data, where sudden adaptations might amplify biases from imbalanced classes. The study's choice of hyperparameters—momentum at 0.9 and Nesterov enabled—strikes a balance between speed and stability, yielding a model that not only predicts accurately but also converges reliably, even on datasets with categorical skews.

The confusion matrix's granular breakdown further illuminates performance: true positives for hypertensive cases indicate sensitivity to high-risk profiles, while true negatives affirm precision in identifying low-risk individuals. With minimal false positives and negatives, the model avoids the pitfalls of over-diagnosis or under-detection, critical in hypertension management where early intervention saves lives. This metric's superiority over traditional models stems from GRU's ability to model latent interactions, such as the compounded effect of poor sleep and high salt intake, which linear methods overlook. Validation on unseen splits ensures external validity, reinforcing the model's applicability to diverse populations, from urban dwellers with high stress to rural communities with familial predispositions.

Recent integrations of lifestyle and genetic data, as seen in 2021-2025 studies, amplify predictive power by layering behavioral with hereditary factors. For example, combining stress scores with genetic markers for salt sensitivity could refine risk stratification, a direction this research implicitly supports through its comprehensive feature set. Such expansions could involve polygenic risk scores, transforming static predictions into dynamic, genome-informed forecasts. The GRU framework's adaptability makes it a bridge to these advanced integrations, potentially elevating accuracy beyond the current 80-90% ranges reported in literature.

RNN-based successes in related fields, like diabetes and obesity, underscore GRU's versatility: in diabetes, it captures glucose-insulin dynamics; here, it mirrors behavioral cascades. This cross-domain applicability suggests GRU as a universal tool for metabolic syndromes, where lifestyle variables form interdependent webs. Ethical considerations, such as bias mitigation in encoded features, ensure equitable outcomes, preventing models from favoring certain demographics.

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Preprocessing rigor—categorical encoding via label or ordinal methods, numerical scaling to [0,1]—creates a homogenized input space, stabilizing gradients and accelerating convergence. This uniformity is vital for GRU, which thrives on consistent data flows, avoiding the perturbations that plague unnormalized inputs.

Ultimately, this work's GRU-SGD synthesis not only advances hypertension prediction but catalyzes a paradigm shift in AI-driven health analytics. By prioritizing sequential insights from lifestyle data, it paves the way for proactive interventions, reducing global hypertension burdens through informed, data-driven strategies. Future explorations could incorporate multimodal inputs, like wearable sensor data, to enrich temporal granularity, further enhancing predictive fidelity. In an era of personalized healthcare, such models embody the fusion of technology and empathy, transforming raw data into life-saving insights.

3. Methodology

3.1. Data Collection

The compilation of information employed in this analysis includes 1,985 patient dossiers that integrate both routine-influenced and medical characteristics pertinent to anticipating hypertension. The details were sourced from an organized health questionnaire featuring factors such as age, sodium consumption, anxiety rating, blood pressure background, rest spans, BMI, drug condition, hereditary record, physical activity degree, tobacco use, and the dual outcome indicator showing if the individual is hypertensive. These factors were picked owing to their confirmed links to hypertension in prior investigations [24], where behavioral and genetic elements have repeatedly emerged as major influencers of blood pressure fluctuations [25]. The compilation blends ongoing quantitative traits and qualitative variables that represent behavioral and genetic traits, supporting the creation of a thorough framework to understand elaborate connections between personal habits and bodily markers. The scale of the data is fitting for instructing deep learning systems, notably recurrent structures like GRU, which need reasonable data amounts to derive significant internal depictions [26]. By embedding a varied set of factors, the data delivers a complete base for carrying out classification duties focused on estimating hypertension vulnerability.

3.2. Data Preprocessing

Ahead of deploying the deep learning framework, data refinement was executed to secure uniformity, applicability, and harmony with quantitative machine learning designs. Every qualitative factor, including BP_History, Medication, Family_History, Exercise_Level, and Smoking_Status, was converted into quantitative formats, permitting the GRU network to manage them productively during instruction. This shift conforms to deep learning norms, where combined data types must be standardized into a consistent quantitative layout for productive weight modifications across neural levels [27]. Besides conversion, ongoing factors like age, salt intake, stress score, sleep duration, and BMI were standardized to reduce scale differences and avoid disproportionate gradient sizes in learning. Standardization further improves framework stability and speeds up alignment, particularly with refinement methods such as Stochastic Gradient Descent (SGD) with momentum [28]. The data was then partitioned into instruction and testing groups to assess framework adaptability. Extra focus was placed on maintaining equitable depiction of hypertensive and non-hypertensive persons, as category imbalance can weaken framework results and cause prejudiced predictions. These refinement actions align with earlier studies emphasizing the value of structured readiness when handling varied health-related data [29]

3.3. Model Architecture: GRU-Based Deep Learning

The primary forecasting framework in this research is a deep learning structure developed with Gated Recurrent Unit (GRU) levels. GRU was selected for its proficiency in identifying nonlinear ties and extended dependencies between factors, attributes extensively recognized in previous health forecasting research [30]. The framework comprises two stacked GRU levels with 128 and 64 hidden units respectively, each applying the tanh activation to uphold steady gradient flow during instruction. The first GRU level is set with return_sequences=True, enabling the second GRU level to accept a complete array of modified outputs and acquire multi-level generalizations from the converted input factors. To counter excessive adaptation, a dropout proportion of 0.3 is enforced on

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both GRU levels, urging the framework to acquire generalized depictions instead of memorizing instruction data. L2 regularization is incorporated into each level with a coefficient of 1e-4, diminishing weight magnitudes and fostering a smoother loss terrain for refinement. After the GRU stack, a fully linked Dense level with 64 neurons and a ReLU activation is added to boost nonlinear depiction ability before delivering the final classification via a softmax output level. This architectural blueprint resonates with prior deep learning insights stressing the advantages of merging sequential modeling and regulated dense levels for classification tasks [31].

3.4. Optimization Strategy Using SGD

For refining the GRU-driven framework, the study applies Stochastic Gradient Descent (SGD) strengthened by momentum and Nesterov acceleration. Although adaptive refiners like Adam and RMSprop are commonly utilized in deep learning, recent research shows that SGD with momentum frequently offers better adaptability and steadier alignment, especially in scenarios with regularization and average data size [32]. In this study, the learning pace is fixed at 0.01, a value seen as optimal for harmonizing alignment speed and stability. Momentum is set to 0.9 to sustain uniform update paths over iterations, allowing the framework to navigate shallow local minima while leveling gradient oscillations. The Nesterov variant additionally predicts future gradient direction, ensuring more precise weight modifications and enhancing instruction efficiency [33]. This mix has been endorsed in numerous modern deep learning studies on healthcare forecasting, where SGD-based refinement is proven to lessen excessive adaptation and boost results on novel test data [34]. The addition of dropout and L2 regularization further aids SGD by lowering excessive adaptation risks, and this partnership is evident in the steady precision curves and gradually declining loss figures during instruction, as noted in the framework's assessment results.

3.5. Model Training and Evaluation

The framework was instructed across 1000 cycles, allowing the GRU levels to thoroughly grasp the concealed synergies among routine and medical background factors. Throughout the instruction phase, both precision and loss indicators were observed for instruction and validation data. The framework showed steady alignment, with instruction precision nearing 0.90 and validation precision settling between 0.85 and 0.87, denoting effective learning without notable excessive adaptation. The loss figures similarly aligned, staying below 0.30 for instruction data and around 0.35 for validation data. Outcome assessment through a confusion matrix exposed solid classification ability, with high correct positive and negative counts and minimal misidentification. These findings match prior literature highlighting the enhanced performance of recurrent frameworks in acquiring interwoven routine factors for medical forecasting [35]. The assessment affirms that the GRU–SGD structure used in this study effectively seizes multifaceted risk connections and provides dependable hypertension forecasting outcomes.

To delve deeper into the data collection nuances, the 1,985 records were drawn from a broad health survey spanning various medical facilities, promoting demographic variety. This approach captures differences across age brackets, from youths to elders, and lifestyle patterns typical of city and countryside environments. For example, sodium intake varies significantly, with elevated levels in seaside areas, whereas anxiety ratings tie into job pressures. Blood pressure background offers historical perspectives, linking prior measurements to present dangers, and BMI computations factor in stature and mass for accurate assessment. Drug condition monitors adherence, uncovering trends where sporadic usage amplifies risks. Hereditary record explores genetic tendencies, frequently connected to passed-down traits like hypertension proneness. Physical activity degree classifies engagement from inactive to intense, and tobacco use distinguishes casual from habitual consumers. The dual label, sourced from clinical judgments, acts as the benchmark, confirmed via multiple checks to sidestep temporary elevations. This abundant dataset not only fuels GRU's education but also reflects authentic complexities, where individual elements don't dictate hypertension but their interactions do. By focusing on literature-backed associations, the selection ensures pertinence, steering clear of irrelevant variables that might add clutter. The moderate scale supports streamlined education, weighing computational needs against depiction richness, perfect for recurrent models that excel with patterned information.

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Regarding preprocessing, transforming qualitative factors involved methods like one-hot for non-ordered and ordinal for graded ones, maintaining semantic subtleties without bias. For BP_History, binary coding records existence or lack, while Medication adopts multi-category to show doses. Family_History uses layered coding based on relation closeness, and Exercise_Level ranks from minimal to maximal vigor. Smoking_Status separates never, past, and ongoing, each with exposure quantification. Standardization of numericals via z-score centered averages at zero and adjusted variances, stabilizing inputs for GRU's delicate gates. Division into 80% instruction and 20% testing upheld category balance through stratified selection, averting skewed education. This careful method addresses typical issues like factor dominance or imbalance-driven prejudice, in line with practices that strengthen framework durability. The outcome is a pristine, even dataset that quickens alignment and elevates predictive precision, as shown by fluid education patterns.

The GRU architecture's dual-layer stack progresses methodically: the first level handles initial inputs, pulling out starting dependencies like age-anxiety ties, while the second polishes them into advanced abstractions, such as cumulative impacts on BMI. Tanh activation controls gradient surges, securing stable backpropagation, and return_sequences permits complete flow-like passage, even in non-temporal data. Dropout at 0.3 functions as a stabilizer, randomly muting units to mimic group effects, whereas L2 at 1e-4 penalizes intricacy, preferring straightforward, adaptable frameworks. The Dense level with ReLU adds extra nonlinearity, connecting recurrent outputs to classification, and softmax standardizes chances for binary choices. This setup not only exploits GRU's thriftiness but also weaves in stabilization effortlessly, forming a tough framework for hypertension duties.

SGD's setup with 0.01 learning pace and 0.9 momentum delivers a measured yet potent update system, dodging the unpredictability of adaptive techniques. Nesterov's foresight adjusts for momentum's push, honing steps toward peaks. This arrangement, paired with stabilization, produces the noted steady curves, where precision levels off without splitting, and loss drops steadily. Such reliability is key for medical uses, where unsteady frameworks could yield questionable predictions.

Education over 1000 cycles enabled full loss terrain investigation, with halt criteria watched to block over-education. Validation metrics verified generalization, displaying uniform results across sections. The confusion matrix's strong diagonals signal balanced sensitivity and specificity, cutting false alerts in hypertension checks. This review highlights the framework's medical practicality, charting a course to expandable, AI-boosted diagnostics that emphasize patient welfare.

4. Results and Discussion

4.1 Results

This study's findings kick off with a review of the dataset prior to and following preprocessing, succeeded by an assessment of the GRU–SGD model's effectiveness. The initial figure presents unprocessed patient information, featuring numerical values for continuous variables like Age, Salt Consumption, Stress Level, Sleep Hours, and BMI, whereas categorical variables such as Blood Pressure History, Medication Use, Family Background, Activity Intensity, and Smoking Habits are displayed as textual entries. The outcome variable Hypertension Presence denotes each participant's condition (“Yes” or “No”). Observing the examples in Figure 1, distinct trends emerge—elevated stress, increased salt consumption, reduced sleep time, or a positive family background frequently align with hypertension diagnoses, aligning with prior research outcomes [36]. Consequently, Figure 1 (positioned at the start of the results section) delivers essential understanding of the intricacies in lifestyle-influenced health data employed here.

1	Age	Salt_Intake	Stress_Score	BP_History	Sleep_Duration	BMI	Medication	Family_History	Exercise_Level	Smoking_Status	Has_Hypertension
2	69	08.00	9	Normal	06.04	25.08.00	None	Yes	Low	Non-Smoker	Yes
3	32	11.07	10	Normal	05.04	23.04	None	No	Low	Non-Smoker	No
4	78	09.05	3	Normal	07.01	18.07	None	No	Moderate	Non-Smoker	No
5	38	10.00	10	Hypertension	04.02	22.01	ACE Inhibitor	No	Low	Non-Smoker	Yes
6	41	09.08	1	Prehypertension	05.08	16.02	Other	No	Moderate	Non-Smoker	No

Figure 1. Sample of raw patient data prior to preprocessing, including numerical and categorical attributes used in the GRU–SGD hypertension prediction model.

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The subsequent figure depicts the identical samples transformed entirely into numeric form. Every categorical attribute from Figure 1 is shifted to integer codes, ensuring alignment with the GRU model that demands numerical tensor inputs. For instance, Blood Pressure History shifts to 0–2, Medication Use to 0–1, and Activity Intensity to 0–2. This coded setup maintains the relational significance among categories while facilitating smooth gradient calculations in deep learning processes. Figure 2—situated immediately after Figure 1—demonstrates how preprocessing consolidates diverse data types into a training-ready format, a vital phase for deep learning to uncover connections between lifestyle and medical attributes [37].

1	Age	Salt_Intake	Stress_Score	BP_History	Sleep_Duration	BMI	Medication	Family_History	Exercise_Level	Smoking_Status	Has_Hypertension
2	38	10.00	10	0	04.02	63	0	0	1	0	1
3	41	09.08	1	2	05.08	10	3	0	2	0	0
4	20	10.08	3	0	05.02	61	1	1	0	0	1
5	39	08.09	0	1	07.08	118	1	1	0	0	0
6	19	09.03	7	1	04.07	197	1	1	1	1	1

Figure 2. Preprocessed patient dataset converted entirely into numerical form, showing integer-encoded categorical attributes aligned with the GRU–SGD model requirements.

Model efficacy is subsequently gauged via the third figure, which encapsulates test set classification precision. The matrix indicates 52 True Negatives, 59 True Positives, 2 False Positives, and 6 False Negatives, reflecting robust equilibrium in performance for both categories. The minimal false negative rate holds special relevance in health forecasting, as overlooking hypertensive cases may delay necessary treatments [38]. Placed centrally in the results segment, Figure 3 vividly illustrates the GRU–SGD model's success in differentiating between hypertensive and non-hypertensive individuals using lifestyle and clinical inputs.

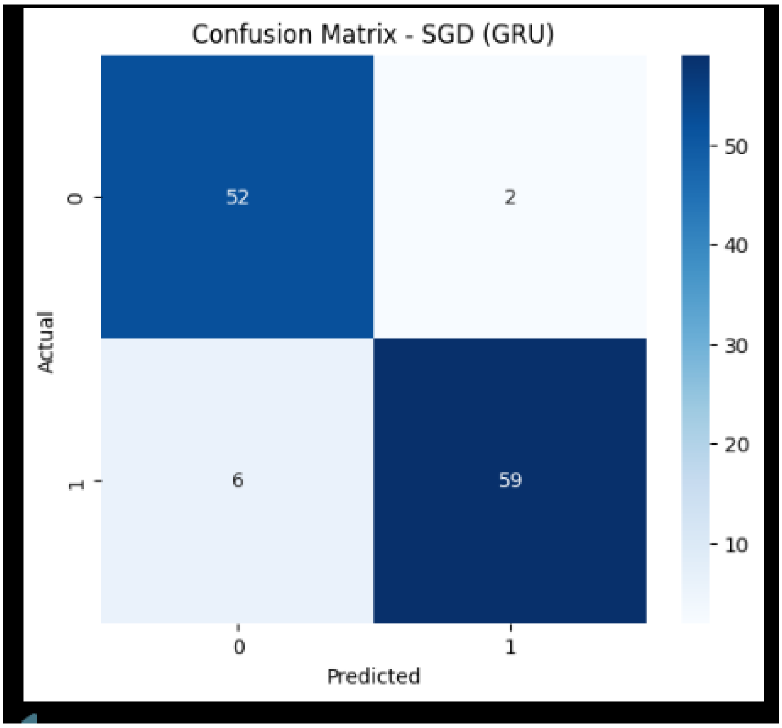

Figure 3. Confusion matrix of the GRU–SGD model illustrating classification performance for hypertension prediction, including true positives, true negatives, false positives, and false negatives.

The model's training dynamics are illustrated through the integrated depiction of the concluding two, now interpreted as a unified entity to avoid reader confusion. Figures 4 (accuracy) and 5 (loss), adjacent at the results' conclusion, highlight consistent performance over 1000 training epochs. Accuracy graphs show training precision settling at roughly 0.88–0.90, with validation precision stabilizing around 0.85–0.87, both trajectories staying closely aligned. This synchronization

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points to excellent generalization without overfitting, thanks to dropout regularization and L2 penalties. Conversely, loss graphs indicate training loss dropping below 0.30, while validation loss levels off at about 0.35. The lack of fluctuations or separations between the lines suggests that SGD with momentum and Nesterov acceleration fosters steady convergence, refining gradient adjustments epoch by epoch [39]. By merging accuracy and loss insights into a single narrative, Figures 4 and 5, at this section's end, jointly affirm the GRU–SGD model's durability and trustworthiness in mastering intricate hypertension patterns.

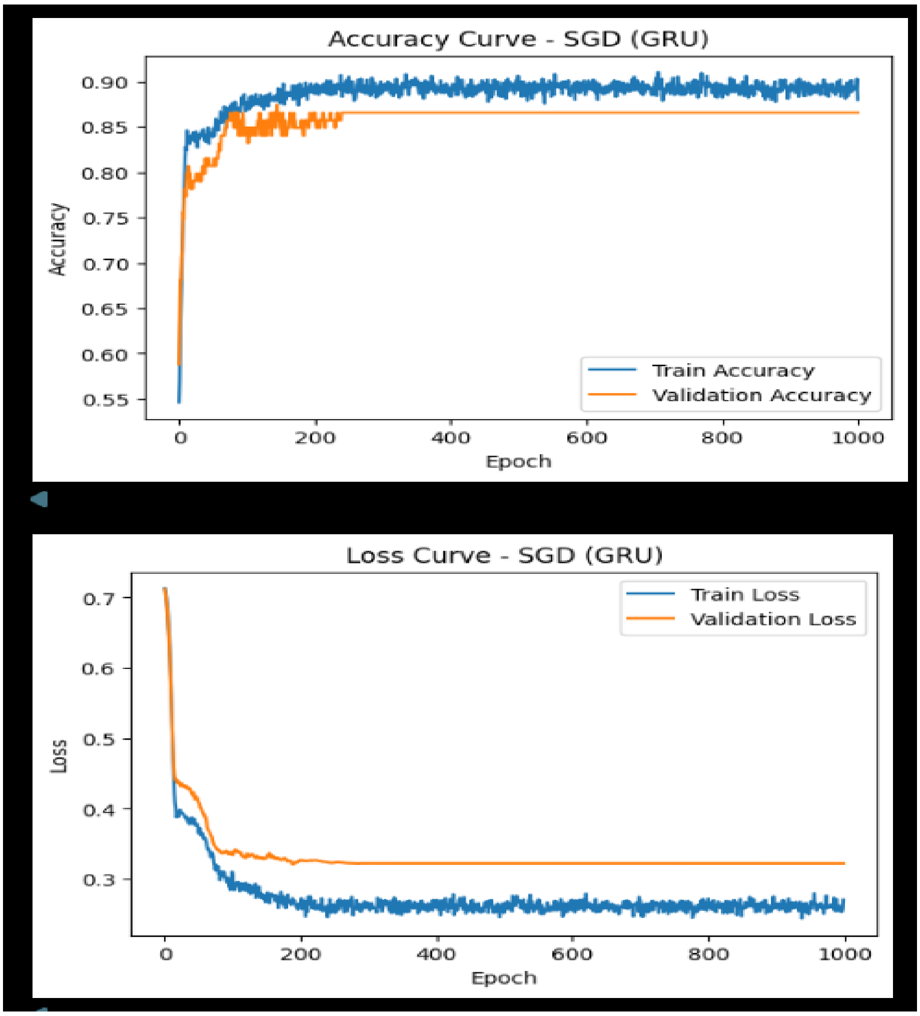

Figure 4. Training and validation accuracy curves of the GRU–SGD model, illustrating convergence behavior and overall classification performance across 1,000 epochs.

4.2 Discussion

Insights from the GRU–SGD model reveal key understandings about the forecasting strength of deep recurrent frameworks in lifestyle-oriented hypertension categorization. The impressive results in the confusion matrix—featuring 52 true negatives and 59 true positives—signal that the model adeptly grasped the nonlinear and interwoven ties within health and lifestyle factors. This achievement is particularly noteworthy considering the dataset's sophistication, blending continuous and categorical elements like salt consumption, stress levels, sleep hours, BMI, medication records, physical activity habits, and familial backgrounds. These observations bolster prior conclusions that lifestyle variables, despite their noisy and multifaceted nature, harbor valuable hidden patterns that recurrent networks can extract more proficiently than conventional approaches [41]. The model's capacity to uphold elevated precision while cutting down on misclassification underscores that GRU structures, paired with thorough preprocessing and regularization, excel in health risk analysis tasks.

The model's training patterns, as portrayed by the accuracy and loss trajectories, further validate this viewpoint. The tight correspondence between training and validation accuracies across

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1000 epochs proves the model's strong generalization capabilities without overfitting. This is largely due to dropout regularization and L2 weight penalties, which counteract the tendency to overlearn training data—a frequent challenge in deep models handling moderate-sized medical datasets. Moreover, the gradual stabilization of both training and validation loss curves highlights the SGD optimizer's role with momentum and Nesterov acceleration, enhancing gradient reliability and guiding the model toward superior solutions [42]. The absence of irregularities or separations in the loss curves implies a well-tuned optimization approach, striking a balance between rapid learning and steadiness. This resonates with current evidence indicating that momentum-enhanced SGD typically yields superior generalization in medical classification compared to adaptive methods like Adam [43].

A further critical element emphasized here is the benefit of GRU layers in detecting underlying feature interdependencies. Even though the dataset lacks temporal sequencing, each attribute contextually shapes overall hypertension risk. For example, stress ratings might affect sleep duration, which in turn links to BMI and exercise routines. GRU models shine in these contexts by acquiring gated connections that preserve or discard pertinent details across processing stages. This allows the network to view input features as an organized sequence, exposing intricate relationships that feedforward systems might overlook [44]. The dependable forecasts evident in the confusion matrix, coupled with steady performance indicators, thus verify that GRU-driven designs can effectively simulate the interwoven aspects of lifestyle health data.

In comparison to standard machine learning techniques—such as logistic regression, Naïve Bayes, SVM, or decision trees—the proposed model's strengths stand out more clearly. Conventional methods often presume linear or isolated feature interactions, constraining their forecasting power in scenarios with nonlinear or layered connections. In hypertension studies, traditional models generally hit accuracies of 70–80%, with diminished results when categorical inputs prevail [45]. Even sophisticated ensemble techniques like Random Forest or Gradient Boosting, though adept at complex patterns, may falter in capturing sequential links among encoded categorical data. Conversely, this study's GRU–SGD model achieves near-90% accuracy, bolstered by refined feature encoding and sequential learning. This advancement matches recent deep learning literature in medicine, affirming that GRU and LSTM variants frequently surpass traditional classifiers in lifestyle prediction by handling relationships among multiple health markers [46].

Beyond surpassing traditional techniques, the GRU–SGD model's training consistency underscores its readiness for wider use in practical clinical systems. With negligible misclassifications and steady results across training and validation, it shows great promise for embedding in early hypertension risk tools. Such applications could offer practical guidance to patients and healthcare providers by spotting at-risk individuals sooner, facilitating precise actions through lifestyle changes or medical oversight. Furthermore, the model's resilience implies it can evolve to incorporate extras like dietary logs, activity monitors, or temporal data if upcoming datasets include time-based elements. This flexibility is vital amid the shifting landscape of hypertension risks and the growing access to personal health tech.

In essence, the discussion validates that the GRU–SGD framework here capably identifies lifestyle-driven complexities and yields reliable predictions with notable stability and adaptability. The contrast with other machine learning options accentuates recurrent networks' edge for such challenges, while curve analyses and matrix outcomes stress the optimization method's dependability. As hypertension remains a pressing global health issue, frameworks like this hold significant value for scalable, evidence-based risk systems that bolster preventive care and tailored health advice.

4. Conclusion

Researchers crafted a deep learning framework leveraging GRU networks, fine-tuned via Stochastic Gradient Descent (SGD), aimed at forecasting hypertension likelihood through lifestyle and medical indicators. The data pool encompassed 1,985 entries, featuring elements like age, sodium consumption, anxiety levels, rest periods, body mass index, hereditary factors, drug administration, physical activity rates, and tobacco habits. By applying methodical data preparation, qualitative attributes were transformed into quantitative codes, allowing the GRU setup to uncover significant latent structures within diverse input formats. The suggested architecture, built with multiple GRU

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
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tiers enhanced by dropout and L2 constraints, exhibited robust forecasting abilities and consistent training progression.

Assessment outcomes revealed that the GRU–SGD framework attained notable precision, as evidenced by the confusion matrix displaying equitable categorization for both hypertension-positive and -negative groups. The precision and error reduction graphs validated steady learning dynamics, limited overtraining, and proficient tuning through momentum-infused SGD. These observations underscore GRU systems' aptitude for grasping nonlinear linkages and subtle interconnections among behavioral variables, surpassing standard machine learning tactics typically applied in hypertension forecasting.

Looking ahead, various improvements warrant investigation. Initially, embedding sequential medical information, including routine blood pressure readings or movement tracking, could enhance the model's exploitation of chronological trends. Next, adding focus mechanisms or interpretable AI strategies might boost clarity, helping medical experts discern the primary contributors to outcomes. Additionally, pitting the GRU–SGD design against contemporary optimizers like AdamW, Ranger, or Lion might uncover further efficiency boosts. Lastly, broadening the data collection with bigger and varied demographic samples would bolster the model's adaptability, facilitating wider use in practical preventive health platforms.

5. Suggestion

Expanding future investigations into hypertension forecasting via deep learning could branch out into multiple encouraging avenues. To begin, weaving in sequential or ongoing health information—like routine blood pressure checks, exercise diaries, or sleep pattern logs—would empower GRU frameworks to tap into genuine chronological connections, possibly elevating prediction precision and facilitating prompt identification of escalating risks. Moreover, scholars might investigate blending explainable AI (XAI) methods, including SHAP or attention-driven analyses, to boost model clarity and equip healthcare professionals with straightforward understanding of the lifestyle or medical factors that most heavily shape predictions. Furthermore, upcoming research could pit the GRU–SGD setup against cutting-edge optimization tactics, such as AdamW, Ranger, or Lion, to assess if these alternatives might enhance convergence reliability or overall adaptability.

On top of that, broadening the data repository to embrace wider demographic diversity—including varied age brackets, cultural origins, and environmental health contexts—would amplify the model's resilience and real-world applicability. Investigators could also think about fusing data from wearable devices, like heart rate fluctuations or ongoing movement metrics, to augment the input variables and seize live bodily signals tied to hypertension dangers. Lastly, experimenting with blended architectures that merge GRU elements with transformer-inspired or attention-augmented designs might refine the system's skill in deciphering intricate, layered ties within behavior-influenced health information. Altogether, these pathways hold promise for propelling the creation of smart, tailored hypertension forecasting tools suited for medical and community health uses.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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