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作品名稱 SAFE_MEDICATION – A STUDY OF USING ARTIFICIAL INTELLIGENCE TO RECOGNISE MEDICATION ERRORS

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ABSTRACT

Medication errors in patients are a global problem. They can negatively affect patients and be costly for hospitals and medical clinics. In 2021, a 28-year-old man with heart problems was admitted to a hospital in Porto Alegre. Due to a pharmacy error and insufficient monitoring in the administration, he received a dose 10 times higher than prescribed. This caused serious and probably irreversible damage to the patient. Reading the news and following the case in the media has encouraged research in scientific databases, searching for information and data on medication errors, as well as emerging technologies to reduce the occurrence of adverse medication events. Based on the findings of an English study that proved that errors occur at the drug prescription stage, the first stage of this research focused on drug dosage errors. The aim of this study is to develop an application based on artificial intelligence that can recognise these errors and help prevent them. The application uses a neural network to analyse prescriptions and warn of possible cases of incorrect dosage. The computer program was developed using a neural network and the drug dosage error recognition system using Python and Keras. The system was trained with 10 drugs and correct and incorrect dosage cases. A graphical interface was created to input and display new case data. Neural networks with different configurations were tested to obtain high accuracy with the training and validation data. A confusion matrix was used to assess the accuracy of the network for cases not used for training. The accuracy was approximately 96%, but problems were found in certain intervals. The errors are due to the need for more training, higher processing capacity and a cloud server. The results of the first stage of the research indicate the feasibility of using a neural network to recognise medication dosage errors and thus preventing the associated risks. Such a method could prevent cases like the one in Porto Alegre. Future studies could incorporate more types of drugs, allergies, drug interactions, pre-existing illnesses and other relevant factors into the system.

Keywords: Medication error; Posology; Artificial intelligence; Neural network; *Python*.

1 INTRODUCTION

Medication errors in patients are a global problem. They harm patients and are costly for hospitals and medical centres. A recent survey conducted in England estimates that 237 million adverse drug events occur every year. These adverse events include adverse drug reactions, allergic reactions and overdoses. The research estimates that these events cost £98,462,582, occupy 181,626 bed-days and contribute to 1,708 deaths annually (ELLIOTT et al., 2021).

Another survey highlights a report by the Institute of Medicine that indicates that there is an "epidemic of medical errors", with the most common type of preventable medical error being medication errors (LARIOS DELGADO et al., 2019). The study further estimates that medication errors can result in more than 1.5 million injuries and more than US$ 3.0 billion in costs arising from the complications of these errors (LARIOS DELGADO et al., 2019). Moreover, data published in the literature suggest that medication errors in Malaysia have been increasing in recent years (SALLEH; ABDULLAH; ZAKARIA, 2020). Impact analyses justify the need to focus on finding solutions, given that the costs of such errors could reach US$42 billion worldwide (KRUSE et al., 2021).

Furthermore, the literature indicates that medication errors occur in administration (54%), prescription (21%) and dispensing (16%) (ELLIOTT et al., 2021). A further study into the clinical process of prescribing medicines suggests that handwritten prescriptions may be responsible for medication errors and a decrease in patient safety (FARGHALI; BORYCKI; MACDONALD, 2021) and that the lack of availability of drug monitoring can affect the ability to intervene immediately with patients (LEE; YOUM, 2021).

1.1 Justification

In 2021, a 28-year-old man was hospitalised with heart problems in the city of Porto Alegre (in the state of Rio Grande do Sul, Brazil). During the hospitalisation process, the pharmacy made a mistake in separating the prescribed medication, giving the nurses a dosage 10 times higher than the one prescribed. This error, combined with an insufficient checking process during the administration, resulted in severe and probably irreversible damage to the young patient (AGEITOS, 2022). Reading the news and following the case through the media encouraged research into scientific databases, looking for information and data on medication errors, as well as emerging technologies to prevent medication errors or adverse medication events.

The literature review identified that measures to address the problem of medication errors are a priority for many medical organisations because of the harmful effects on patients, high costs and many deaths (ELLIOTT et al., 2021; KRUSE et al., 2021; LARIOS DELGADO et al., 2019). The American Institute of Medicine concludes that an improved use of information technology can be an essential step in reducing medication errors (LARIOS DELGADO et al., 2019). Similarly, the Department of Health and Social Care in England has been endeavouring to identify the number of cases with errors and the burden of these errors (ELLIOTT et al., 2021). Furthermore, the integration of artificial intelligence (AI) into clinical workflows is recommended (LARIOS DELGADO et al., 2019). In medicine, machine learning and neural networks have been applied to diagnosis (CHARY; BOYER; BURNS, 2021; LI et al., 2022), and big data analytics, Internet of Things (IoT), AI and cloud combined with medical expertise are applied to convert information into digital data (LEE; YOUM, 2021).

The high global impact of medication errors and the identified lack of availability of frequent medication monitoring that led to medication errors in the aforementioned case justify a study on the use of AI to recognise medication errors.

1.2 Problem

To propose a solution to the problem, this research investigates the following question: "How can an application be developed to help recognise possible cases of posology errors?"

1.3 Objective

To answer the research question, the following research objective emerged: "To develop a computer program based on artificial intelligence capable of identifying possible cases of medication posology errors".

2 LITERATURE REVIEW

The literature on medication errors indicates that health services face challenges in performing the processes of prescribing and administering medicines. To address the problem, it is recommended to understand the reasons medication errors occur (ELLIOTT et al., 2021) and to encourage the use of emerging technologies to mitigate the risk of medication errors (LARIOS DELGADO et al., 2019).

2.1 Why do medication errors occur?

According to a survey conducted in the healthcare system in England, medication errors may occur at many stages of patient care, from ordering the medication to the moment the patient receives it. In general, most medication errors occur at one of the following points: administration (54%), prescription (21%) and dispensing (16%)(ELLIOTT et al., 2021). An analysis performed on 168 records of medication administration errors identified the following causes: wrong dose (27%), wrong drug (18%), wrong route (15%), delay/omission (14%), wrong patient (8%) and poor technical skills (8%) (“Did you know?”, [s.d.]).

Moreover, the literature indicates that the lack of current knowledge about medicines approved by regulatory bodies and the generalised growth in prescribing and consumption of medicine contribute to an increase in medication errors (LARIOS DELGADO et al., 2019). The dynamic of insufficient time for knowledge updates or the lack of information contributes to an increase in the workload, which has a negative impact on the quality of care and turnover among professionals (KRUSE et al., 2021). In addition, the indiscriminate use of medical jargon and implicit guidelines in prescriptions increases the challenges for nursing teams, increasing the risk of misunderstanding prescriptions, which can lead to an elevated risk of medication errors (LI et al., 2022).

The literature review indicated that medication errors occur primarily in the process of administering the medication. The lack of technological support contributes to the occurrence of medication errors. The widespread use of AI programs could help facilitate access to and updating of new medications, decrease the risk of misunderstanding medical prescriptions and reduce the stress on medical and nursing staff. The following section describes ways to mitigate medication errors using emerging technologies.

2.2 How can medication errors be mitigated through emerging technologies?

The literature suggests various processes and emerging technologies to mitigate medication errors. The identified actions suggest focusing on eliminating manual processes and controls, using emerging digital technologies (big data analysis, IoT, AI, machine learning and deep learning) and dashboards and investing in decision-support systems.

First, the literature suggests that the risks of medication errors may be mitigated by increasing the capacity to deal with the enormous amount of information and data available. In this sense, the focus should be on linking and identifying errors, particularly, identifying which errors persist in the medication administration process and their impact on patients (ELLIOTT et al., 2021; WANG et al., 2019). For example, a real-time hospital information system (HIGEA) generates specific alerts to prevent medication errors. As soon as a new drug is prescribed or new information is received from manufacturers, the system automatically activates or deactivates the alert. This system transforms a "standard" data structure into a NoSQL database, where all the information on a particular patient is stored as a document (IBÁÑEZ-GARCIA et al., 2019). The system aims to improve documentation levels without significantly altering the nursing time spent on most activities, since improved documentation results in safer prescriptions (KRUSE et al., 2021). Another important point is the replacement of handwritten prescriptions with electronic ones (EL-NAHAL et al., 2022; FARGHALI; BORYCKI; MACDONALD, 2021).

AI-enabled apps can provide general information about medicines that help doctors and nurses administer the correct medication. Nevertheless, finding a medicine in such apps can require much time and effort. An example of such an app is the "e Nurses' Guide system", which focuses on drug information and nurses' notes (ALHARBI et al., 2021).

Another type of project consists of a wearable expandable health monitoring system, a smart drug distribution system, a cloud-based big data analytical diagnosis and an AI-based reporting tool. The system has demonstrated the ability to achieve the objectives for which it was designed by using IoT to relieve pressure on hospitals due to overcrowding and to reduce delays in healthcare services (LATIF et al., 2020).

A system for avoiding errors and improving the quality of home care services has also been proposed. The solution comprises a multi-agent system based on reinforcement learning and deep learning algorithms (NAEEM; PARAGLIOLA; CORONATO, 2021) and a method in which videos of patients taking medication are recorded using a camera image sensor integrated into a wearable device. The collected data are used as a dataset for the training of the latest convolutional neural network technique (LEE; YOUM, 2021).

Further studies suggest applying AI-based infrastructure to reduce medication errors when following a treatment plan at home (NAEEM; CORONATO, 2022) and a machine learning approach to simplify prescription instructions automatically and reliably into patient-friendly language (LI et al., 2022).

Educational videos about medication may influence psychological well-being, improve confidence in administering medication and reduce medication errors (ADELEYE et al., 2022). A deep learning application may reduce avoidable errors and the associated risk by correctly identifying prescription drugs. The app identifies prescription pills from moving images in the NIH NLM Pill Image Recognition Challenge dataset and recognises the correct pill within the first five results with 94% accuracy (LARIOS DELGADO et al., 2019).

Complete patient control may contribute to avoiding medication errors. The ieMR platform covers the process from admission to discharge and includes six modules from an enhanced computerised medical order entry system, pharmaceutical care, holistic care, bedside display, optimally personalised medication discharge plan and pharmaceutical care record system (HUNG et al., 2021).

AI systems for healthcare may potentially fail. To avoid such errors, we suggest a framework for auditing medical algorithms that guides the auditor through a process of considering possible algorithmic errors in the context of a clinical task, mapping the components that can contribute to the occurrence of errors and anticipating their possible consequences. (LIU et al., 2022).

A further action to improve control is the implementation of dashboards. Dashboards provide regularly updated audit information and may be an important contributor to medication security in primary care (WILLIAMS et al., 2018). Additionally, decision-support systems and digital personal assistants may alert doctors and nurses to avoidable errors (KRUSE et al., 2021; LI et al., 2015). Dashboards allow data to be analysed and the system to be systematically evaluated: in a study, "inadequate dose", "wrong drug" and "wrong time" were the predominant errors, while events with "wrong patient", "wrong dosage form" and "monitoring error" were uncommon (IBÁÑEZ-GARCIA et al., 2019). An online medication safety dashboard allows pharmacists to identify patients at risk of potentially dangerous prescriptions. Subsequently, the focus can shift to resolving risks on a case-by-case basis; however, marked variations in the processes exist between some practices. The workload decreases over time, as the focus shifts to resolving new cases of dangerous prescribing (JEFFRIES et al., 2020). Presenting pop-up alerts with clear recommendations as part of the workflow is an essential feature for success (BAYPINAR et al., 2017).

3 METHODOLOGY

This study is classified as design science research (DSR). DSR is characterised by generating knowledge that is applicable and useful for solving problems, improving systems and creating solutions or artefacts. These artefacts can be defined as constructs, models, methods and snapshots (LACERDA et al., 2013). The study followed the phases of PDS: the problem was identified by the media that publicised the medication error that occurred in Porto Alegre (AGEITOS, 2022); a literature review phase was conducted to find scientific publications that explained the relevance, reasons and emerging technologies to deal with the problem; the problem awareness phase was performed through data collection; the SAFE_MEDICATION artefact phase was structured. Finally, the results of SAFE_MEDICATION were detailed and discussed, along with a presentation of the study's conclusions (DRESCH et al., 2015).

3.1 Literature review phase

A systematic literature review was conducted on the factors that cause medication errors and the emerging digital technologies that can reduce them. The search was based on scientific articles in English from the Scopus database, using keywords related to the topic. Twenty-four articles were selected which contributed to answering the research problem and achieving the proposed objective. The articles were read and coded for data analysis. The aim of the research was to analyse the impacts, causes and solutions to medication errors in healthcare. To this end, a literature review and qualitative analysis of textual data were performed using a coding approach (SALDAÑA, 2015). Coding consists of applying different types of codes to the data, according to the research questions and objectives. Codes can be for example descriptive, inferential, structural and evaluative and can be combined or refined throughout the analytical process. Coding makes it possible to identify patterns, themes, categories and relationships in the data and facilitates the interpretation and communication of the results. Excel spreadsheets were used for coding to facilitate the analysis of the qualitative data in the next stages. The codes were organised based on the impacts of medication errors, their occurrence location and ways to mitigate them through emerging technologies (Figure 1).

Figure 1 – Coding table

	A	B	C
1	**Documento**	**Conteúdo de Citação**	**Códigos**
2	Automated detection of medication administration errors in neonatal intensive care http://dx.doi.org/10.1016/j.jbi.2015.07.012	Automated detection of medication administration errors through the EHR is feasible and performs better than currently used incident reporting systems. Automated algorithms may be useful for real-time error identiffcation and mitigation.	DETECÇÃO AUTOMÁTICA - ALGORITIMO
3	Physicians' Compliance with a Clinical Decision Support System Alerting during the Prescribing Process J Med Syst (2017) 41:	Presenting pop-up alerts as part of the workflow with a clear recommendation is a feature critical to success. Therefore we implemented three algorithms in a clinical decision support system alerting during the medication ordering process. We	CLINICAL DECISION SUPPORT - ALGORITMO
4	96 DOI 10.1007/s10916-017-0717-4	This clinical decision support system that alerts physicians for preventable medication errors during the medication ordering process is an effective ap�proach to improve prescribing behavior.	CLINICAL DECISION SUPPORT - ALGORITMO
5	SMASH! The Salford medication safety dashboard . J Innov Health Inform. 2018;25(3):183–193. http://dx.doi.org/10.14236/jhi.v25i3.1015	We aimed to develop and roll out an online dashboard application that delivers this audit and feedback intervention in a continuous fashion.	AUDITORIA E FEEDBACK - ONLINE DASHBOARD
6		Based on initial system requirements, we designed the dashboard's user interface over three iterations with six GPs, seven pharmacists and a member of the public. Prescribing safety indicators from previous work were implemented in the	AUDITORIA E FEEDBACK - ONLINE DASHBOARD
7		We have developed and successfully rolled out of a complex, phar�macist-led dashboard intervention in Salford, UK. System usage statistics indicate broad and sustained uptake of the intervention. The use of systems that provide regularly	AUDITORIA E FEEDBACK - ONLINE DASHBOARD
8	Understanding Health Information Technology Induced Medication Safety Events by Two Conceptual Frameworks Appl Clin Inform	The term medication error refers to "any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient, or consumer." 30 • Health IT is at	CONCEITO
9	2019;10:158–16	The distribution of the involved error types is shown in ►Fig. 3. "Improper dose," "wrong drug," and "wrong time" were the prevailing errors, whereas events with	ANÁLISE ERROS

Source: Elaborated by the author

3.2 Problem awareness phase

The researcher collected data at a hospital and a geriatric clinic to compare with the literature review. He used various methods, such as interviews, observations, visits, document analysis and messages (WhatsApp). He also triangulated the data sources to ensure the reliability of the data obtained in different ways (EISENHARDT; GRAEBNER, 2007; YIN, 2017). The activities were completed by August 2023. Data were collected through semi-structured interviews with the participants and through document analysis. The interviews were scheduled by email and electronic messaging (WhatsApp) and conducted in person or by exchanging messages via WhatsApp. The author conducted the interviews and recorded all the information reported. One of the interviewees authorised a recording. These notes were later transferred to Microsoft Word for text editing. After each session, the participant was requested to show documents related to the covered topics. These documents are primarily reports that are not public due to patient confidentiality. Photos were allowed, as shown in the figures below. The profiles of the interviewees are shown in Table 1.

Table 1 – Profile of respondents

Organisation	Position of respondents	Education	Years of expertise	Sectors of activity	Length of interviews
Geriatric clinic	Manager	Nursing	15 years	Hospitals and emergency rooms	35 min recorded
Public hospital (Porto Alegre metropolitan area)	Training supervisor	Nursing	8 years	Hospitals	Visiting and exchanging messages via WhatsApp
	Process supervisor	Nursing	10 years	Hospitals and emergency rooms	Visiting and exchanging messages via WhatsApp

Source: Elaborated by the author

The literature review pointed to dosage as one of the most critical factors in the occurrence of medication errors. Similarly, the consulted sources confirmed that there are difficulties in reconciling the process of prescribing, sorting by the pharmacy, checking by the nurses and administering the medication to the patient, which increases the risk of dosage errors. Given this scenario, the first stage of the research focused on identifying and analysing possible cases of medication error in dosage. Furthermore, the interviewees suggested and evaluated the list of medicines that would be used to train the neural network, with the aim of improving the error detection and prevention system.

3.3 SAFE_MEDICATION artefact phase

The AI developed at this stage is created using a neural network from the Keras library in Python. The neural network was selected to simulate the decision-making of a human brain (HAYKIN, 2008), and data taken from the package leaflets were used as input. The aim is to create a neural network that can decide whether a patient's dose of medication is safe. To do this, the neural network is trained with supervised learning, comparing the output generated by the network with the desired output. With this feedback, the weights of the network are adjusted to approach the desired output. The number of layers and neurons in the network is observed to ensure the network's accuracy and functionality for the desired application.

3.3.1 Patient information leaflets

The leaflet is a document that contains technical information about medicines, such as composition, indications, contraindications, posology, adverse reactions, drug interactions and precautions for use. This information is based on scientific studies and regulatory standards and should be updated periodically according to new available evidence. To research the package leaflets, the dosage data were retrieved from the Anvisa website, which is the National Health Surveillance Agency responsible for regulating and supervising medicines in Brazil. Anvisa website provides a public leaflet consultation system, which allows quick and easy access to official information on medicines registered in the country. A search can be performed by trade name, active ingredient, laboratory, or therapeutic class. Additionally, the system allows leaflets to be downloaded in a PDF format, which can be printed or saved for later consultation (**Consultas**).

3.3.2 Python scripts

Python is a programming language that is easy to learn and use, with a simple and readable syntax. It is a free and open-source language, which allows modifications to its source code. Python is versatile and useful for many purposes, from creating web pages and games to AI and neural networks. Python has powerful features in its standard library and in community modules and frameworks, which make it easy to develop robust and innovative solutions (The *Python* Tutorial). The Python Tutorial website provides tutorials on how to create AI and neural network scripts with Python. The tutorial covers the basics of the language, such as data types, control structures, functions, classes, modules and links to other resources and documentation on Python and its libraries.

3.3.3 Training

The aim of SAFE_MEDICATION was to train a neural network to recognise possible cases of medication errors, using a dataset with 20,000 samples, 2,000 for each medication. The training was conducted in 1,000 epochs with a batch size of 10; that is at each iteration of the algorithm, 10 samples were used to calculate the error and update the network parameters. The training evaluation criterion was accuracy, which measures the proportion of samples that were correctly classified by the neural network. Moreover, processing time, which depends on the complexity of the neural network and the size of the dataset, was considered. The challenge was to achieve the best possible accuracy while keeping the processing time reasonable. To this end, different values of the learning rate and different optimisation methods, which seek to find the minimum of the error function, were tested.

3.3.4 Neural network

A neural network is a system designed to recreate, through electronic circuits or a computer program, the way the human brain performs a task. The network is developed by coupling processing units known as neurons. To develop a neural network, the number of inputs, layers, neurons and activation functions are selected to best suit the proposed application (HAYKIN, 2008). SAFE_MEDICATION is an artefact that aims to develop an intelligent system capable of recognising possible cases of medication dosage errors, avoiding incorrect administration and unwanted adverse effects. To do this, the project uses a neural network built using Python's Keras library, a high-level interface to the TensorFlow platform, which specialises in deep neural networks.

Keras is a high-level application programming interface for creating and training deep learning models. Designed for rapid prototyping, cutting-edge research and production, it has three main advantages: ease of use, modularity and extensibility. Keras has a simple and consistent interface optimised for common use cases, which provides clear and practical feedback for user errors. Keras models are made by connecting configurable elements, such as layers, optimisers and loss functions, with few restrictions. Keras also allows the development of customised elements that express new ideas for research, such as new layers, metrics and loss functions. Keras is compatible with various backend platforms, such as TensorFlow, JAX and PyTorch, and can be used both on-premises and in the cloud. Keras is one of the main tools for developing and deploying machine learning-enabled applications. More information can be found on the website About *Keras*.

The neural network used in SAFE_MEDICATION has the following architecture: an input layer with 5 neurons, which represent the characteristics of patients and medicines; a first hidden layer with 128 neurons and a second with 256 neurons, which learns to extract relevant patterns from the input data; and an output layer with 1 neuron, which indicates the probability of a drug interaction or adverse effect occurring. The activation function used in the hidden layers is the rectified linear unit (ReLU), which is a non-linear function that allows complex problems to be modelled. The activation function used in the output layer is sigmoid, which is a function that varies between 0 and 1 and is suitable for binary classification problems.

3.3.5 Analysis

SAFE_MEDICATION is a computer program that uses AI, a neural network, Python scripts and training with correct and incorrect dosages to answer a user's query about the suitability of a medication dosage. The program has a graphical interface created in Python, in which the user can enter their age, weight and the dosage of the medication they want to check. By clicking on a button, the program triggers the neural network, which analyses the input data and compares it with the training cases. The answer is displayed on the interface in the form of a green or red light, similar to a traffic light. If the signal is green, it means that the dosage may be correct, according to the probability of accuracy of the trained neural network. If the signal is red, it means that the dosage may be incorrect, indicating a possible medication error.

The creation of a user interface is important to facilitate interaction with the program, making it more accessible and intuitive. Developed by Tkinter, a Python standard library for use with the Tlc/Tk GUI toolkit. The interface contains fields for entering the medication, weight, age and dosage. In addition, the interface allows the answer to be visualised quickly and clearly, avoiding confusion or doubts. SAFE_MEDICATION is a tool that can help prevent medication errors, contributing to patient safety and quality of care.

4 FINDINGS

The findings were obtained from different neural network configurations. For these different tests, the number of drugs, neurons, hidden layers, epochs, batch size, learning rate and types of activation were altered. The reliability of the developed neural network was checked using a confusion matrix.

4.1 First tests

The initial research findings came from simpler neural network configurations. At first, the technology's performance was tested for a few drugs. To train the neural network, it was determined which data were relevant to the development of the system. For the selected drugs, for example, clonazepam (**Consultas**), a table was developed (Table 2) with the most important data for training, taken from the package leaflet.

Table 2 – Medication data of clonazepam

Patient information	**Maximum dosage**
Ages 0 to 10	0,005 mg/Kg/day
Weight less than 30 kg	0,005 mg/Kg/day
Ages 10 to 16	6 mg/day
Over 16 years old	20 mg/day

Source: Consultas

4.2 Test with 1 and 2 drugs

The relevant configurations for developing the neural network for only one drug (200 cases) were four layers, with the two hidden layers having 12 and 8 neurons, ReLU and Sigmoid activation functions; the training involved a learning rate of 0.0001, 150 epochs and a batch size of 10.

The first test showed the ability of the neural network to learn. Thus, the code was developed for a larger number of drugs. The subsequent test was conducted with 2 drugs (400 cases) and used the same settings as the first test. The purpose of this continued development was to understand the system's response with a larger number of training cases.

As a result of the increase in training cases, the system showed a considerable decrease in accuracy. To understand how to improve the accuracy value, the training values were modified. Thus, the epoch and batch size values were changed in two tests. The epoch value was increased to 300 and the batch size value was increased to 32. Figures 2 and 3 show the training conducted with the neural networks, showing the accuracy values of the system after training of 90.25% and 89.50%.

Figure 2 – Test with 300 epochs

```
Epoch 293/300
40/40 [==============================] - 0s 922us/step - loss: 0.2427 - accuracy: 0.8950
Epoch 294/300
40/40 [==============================] - 0s 869us/step - loss: 0.2186 - accuracy: 0.9050
Epoch 295/300
40/40 [==============================] - 0s 926us/step - loss: 0.2106 - accuracy: 0.8975
Epoch 296/300
40/40 [==============================] - 0s 893us/step - loss: 0.1796 - accuracy: 0.9225
Epoch 297/300
40/40 [==============================] - 0s 949us/step - loss: 0.2464 - accuracy: 0.8900
Epoch 298/300
40/40 [==============================] - 0s 967us/step - loss: 0.2116 - accuracy: 0.9000
Epoch 299/300
40/40 [==============================] - 0s 973us/step - loss: 0.2619 - accuracy: 0.8925
Epoch 300/300
40/40 [==============================] - 0s 971us/step - loss: 0.2009 - accuracy: 0.8950
13/13 [==============================] - 0s 917us/step - loss: 0.2419 - accuracy: 0.9025
Accuracy: 90.25
```

Source: Script Python SAFE_MEDICATION

Figure 3 – Test with a batch size of 32

```
Epoch 143/150
7/7 [==============================] - 0s 2ms/step - loss: 0.2064 - accuracy: 0.9100
Epoch 144/150
7/7 [==============================] - 0s 1ms/step - loss: 0.2088 - accuracy: 0.9075
Epoch 145/150
7/7 [==============================] - 0s 1ms/step - loss: 0.2114 - accuracy: 0.9000
Epoch 146/150
7/7 [==============================] - 0s 1ms/step - loss: 0.2216 - accuracy: 0.8950
Epoch 147/150
7/7 [==============================] - 0s 1ms/step - loss: 0.2298 - accuracy: 0.9050
Epoch 148/150
7/7 [==============================] - 0s 1ms/step - loss: 0.2125 - accuracy: 0.9075
Epoch 149/150
7/7 [==============================] - 0s 2ms/step - loss: 0.2014 - accuracy: 0.9050
Epoch 150/150
7/7 [==============================] - 0s 1ms/step - loss: 0.2290 - accuracy: 0.9075
13/13 [==============================] - 0s 914us/step - loss: 0.2266 - accuracy: 0.8950
Accuracy: 89.50
```

Source: Script *Python* SAFE_MEDICATION

The tests did not show a significant increase in accuracy. Therefore, at this point, it is concluded that the solution to increasing the accuracy value is not related to the training settings.

4.3 Tests with 10 drugs

From the first tests performed, the neural network was found to be able to learn from the training data. Therefore, the number of drugs was increased to 10, bringing the total number of training cases to 2,000. The first test was conducted using the same neural network configurations as in the first tests. Figure 4 shows the training performed with the neural network and, in the end, the system's accuracy (72.75%) when trained.

Figure 4 – Neural network training with 10 drugs

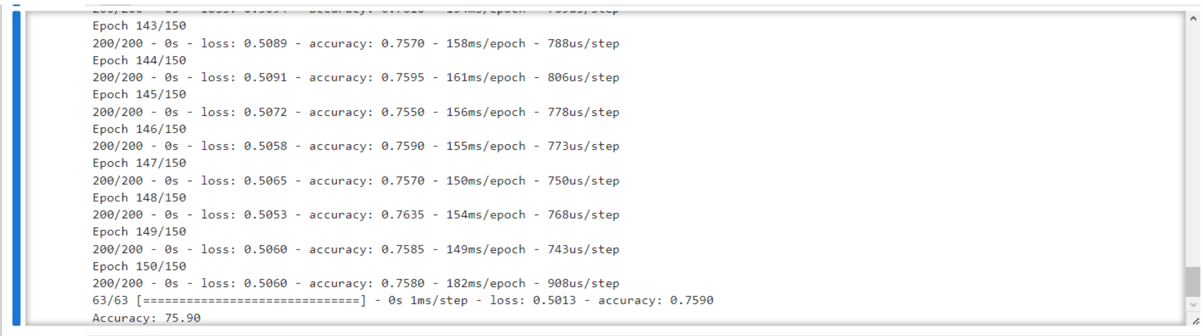
```
model.fit(x, y, epochs=150, batch_size=10, shuffle = True , verbose = 2)
_, accuracy = model.evaluate(x, y)
print('Accuracy: %.2f' % (accuracy*100))
```

```
Epoch 143/150
200/200 - 0s - loss: 0.5160 - accuracy: 0.7625 - 160ms/epoch - 802us/step
Epoch 144/150
200/200 - 0s - loss: 0.5007 - accuracy: 0.7600 - 169ms/epoch - 846us/step
Epoch 145/150
200/200 - 0s - loss: 0.5111 - accuracy: 0.7530 - 168ms/epoch - 841us/step
Epoch 146/150
200/200 - 0s - loss: 0.5129 - accuracy: 0.7485 - 147ms/epoch - 737us/step
Epoch 147/150
200/200 - 0s - loss: 0.5162 - accuracy: 0.7415 - 171ms/epoch - 856us/step
Epoch 148/150
200/200 - 0s - loss: 0.5035 - accuracy: 0.7650 - 160ms/epoch - 798us/step
Epoch 149/150
200/200 - 0s - loss: 0.5104 - accuracy: 0.7620 - 165ms/epoch - 825us/step
Epoch 150/150
200/200 - 0s - loss: 0.5182 - accuracy: 0.7510 - 161ms/epoch - 804us/step
63/63 [==============================] - 0s 871us/step - loss: 0.5337 - accuracy: 0.7275
Accuracy: 72.75
```

Source: Script *Python SAFE_MEDICATION*

This test shows an increase in the number of cases. Nevertheless, the accuracy value decreased. This shows the continuity of the conclusion that when increasing the number of cases in the same neural network, it is necessary to change the configuration values of the code. The first attempt to increase the accuracy value when testing 10 drugs was to add another hidden layer with 5 neurons. Figure 5 shows the training conducted with the neural network and, at the end, the system's accuracy (75.90%) when trained.

Figure 5 – Neural network training with 10 drugs including one additional hidden layer.



```
Epoch 143/150
200/200 - 0s - loss: 0.5089 - accuracy: 0.7570 - 158ms/epoch - 788us/step
Epoch 144/150
200/200 - 0s - loss: 0.5091 - accuracy: 0.7595 - 161ms/epoch - 806us/step
Epoch 145/150
200/200 - 0s - loss: 0.5072 - accuracy: 0.7550 - 156ms/epoch - 778us/step
Epoch 146/150
200/200 - 0s - loss: 0.5058 - accuracy: 0.7590 - 155ms/epoch - 773us/step
Epoch 147/150
200/200 - 0s - loss: 0.5065 - accuracy: 0.7570 - 150ms/epoch - 750us/step
Epoch 148/150
200/200 - 0s - loss: 0.5053 - accuracy: 0.7635 - 154ms/epoch - 768us/step
Epoch 149/150
200/200 - 0s - loss: 0.5060 - accuracy: 0.7585 - 149ms/epoch - 743us/step
Epoch 150/150
200/200 - 0s - loss: 0.5060 - accuracy: 0.7580 - 182ms/epoch - 908us/step
63/63 [==============================] - 0s 1ms/step - loss: 0.5013 - accuracy: 0.7590
Accuracy: 75.90
```

Source: Script Python SAFE_MEDICATION

This attempt to improve the performance of the network did not prove to be as efficient, since it only increased the accuracy by approximately 3%. It was decided to return to the composition of only two hidden layers. To solve the problem of the accuracy decrease caused by the increase in training cases, the number of neurons of the two hidden layers was increased. This modification of the neural network was separated into 3 stages: switching to 32 and 64 neurons, 64 and 128 neurons and 128 and 256 neurons. Figure 6 shows the training conducted with the neural network with 32 and 64 neurons in the hidden layers, resulting in the system being 85.6% accurate after training.

Figure 6 – Training of the neural network with 32 and 64 neurons

```
Epoch 143/150
200/200 - 0s - loss: 0.3479 - accuracy: 0.8300 - 151ms/epoch - 757us/step
Epoch 144/150
200/200 - 0s - loss: 0.3445 - accuracy: 0.8365 - 215ms/epoch - 1ms/step
Epoch 145/150
200/200 - 0s - loss: 0.3354 - accuracy: 0.8290 - 153ms/epoch - 765us/step
Epoch 146/150
200/200 - 0s - loss: 0.3360 - accuracy: 0.8315 - 155ms/epoch - 776us/step
Epoch 147/150
200/200 - 0s - loss: 0.3304 - accuracy: 0.8390 - 158ms/epoch - 789us/step
Epoch 148/150
200/200 - 0s - loss: 0.3338 - accuracy: 0.8405 - 150ms/epoch - 752us/step
Epoch 149/150
200/200 - 0s - loss: 0.3455 - accuracy: 0.8345 - 147ms/epoch - 735us/step
Epoch 150/150
200/200 - 0s - loss: 0.3403 - accuracy: 0.8395 - 149ms/epoch - 745us/step
63/63 [==============================] - 0s 808us/step - loss: 0.3068 - accuracy: 0.8555
Accuracy: 85.55
```

Source: Script Python SAFE_MEDICATION

Figure 7 shows the training conducted with the neural network with 64 and 128 neurons in the hidden layers, resulting in a system training accuracy of 87.6%.

Figure 7 – Training of the neural network with 64 and 128 neurons

```
Epoch 143/150
200/200 - 0s - loss: 0.2981 - accuracy: 0.8635 - 165ms/epoch - 824us/step
Epoch 144/150
200/200 - 0s - loss: 0.2994 - accuracy: 0.8630 - 169ms/epoch - 845us/step
Epoch 145/150
200/200 - 0s - loss: 0.2896 - accuracy: 0.8680 - 177ms/epoch - 886us/step
Epoch 146/150
200/200 - 0s - loss: 0.2931 - accuracy: 0.8630 - 149ms/epoch - 745us/step
Epoch 147/150
200/200 - 0s - loss: 0.2933 - accuracy: 0.8565 - 151ms/epoch - 757us/step
Epoch 148/150
200/200 - 0s - loss: 0.2895 - accuracy: 0.8775 - 149ms/epoch - 745us/step
Epoch 149/150
200/200 - 0s - loss: 0.2964 - accuracy: 0.8615 - 157ms/epoch - 783us/step
Epoch 150/150
200/200 - 0s - loss: 0.2825 - accuracy: 0.8690 - 150ms/epoch - 748us/step
63/63 [==============================] - 0s 1ms/step - loss: 0.2645 - accuracy: 0.8755
Accuracy: 87.55
```

Source: Script Python SAFE_MEDICATION

Figure 8 shows the training conducted with the neural network with 128 and 256 neurons in the hidden layers, resulting in a system training accuracy of 87.1%.

Figure 8 – Training of the neural network with 128 and 256 neurons

```
Epoch 143/150
200/200 - 0s - loss: 0.2510 - accuracy: 0.8860 - 303ms/epoch - 2ms/step
Epoch 144/150
200/200 - 0s - loss: 0.2526 - accuracy: 0.8835 - 196ms/epoch - 979us/step
Epoch 145/150
200/200 - 0s - loss: 0.2609 - accuracy: 0.8885 - 187ms/epoch - 933us/step
Epoch 146/150
200/200 - 0s - loss: 0.2527 - accuracy: 0.8795 - 191ms/epoch - 957us/step
Epoch 147/150
200/200 - 0s - loss: 0.2502 - accuracy: 0.8805 - 196ms/epoch - 979us/step
Epoch 148/150
200/200 - 0s - loss: 0.2558 - accuracy: 0.8820 - 192ms/epoch - 958us/step
Epoch 149/150
200/200 - 0s - loss: 0.2428 - accuracy: 0.8840 - 189ms/epoch - 943us/step
Epoch 150/150
200/200 - 0s - loss: 0.2744 - accuracy: 0.8805 - 189ms/epoch - 946us/step
63/63 [==============================] - 0s 953us/step - loss: 0.2861 - accuracy: 0.8710
Accuracy: 87.10
```

Source: Script Python SAFE_MEDICATION

The tests with the increase in neurons showed that this solved the problem caused by the addition of the training cases. It was shown that this change had an immediate effect but that it was not sufficient to achieve accuracy above 90%. After the tests, the configuration with 128 and 256 neurons was retained so that it would be possible to increase the number of cases later. With the consistency of the accuracy during the development of the last three neural networks, the next test was based on a previously used strategy: increasing the setting values. At this stage, the epoch value was increased to 600 and 1,000 in two tests. Additionally, the learning rate was changed to 0.0005. Figures 9 and 10 show the training conducted with the neural networks, showing the training accuracy of the system at 95.3% and 97%, respectively.

Figure 9 – Neural network training with 600 epochs

```
Epoch 593/600
200/200 - 0s - loss: 0.1643 - accuracy: 0.9250 - 194ms/epoch - 972us/step
Epoch 594/600
200/200 - 0s - loss: 0.1360 - accuracy: 0.9420 - 192ms/epoch - 960us/step
Epoch 595/600
200/200 - 0s - loss: 0.1480 - accuracy: 0.9380 - 192ms/epoch - 958us/step
Epoch 596/600
200/200 - 0s - loss: 0.1399 - accuracy: 0.9415 - 190ms/epoch - 952us/step
Epoch 597/600
200/200 - 0s - loss: 0.1282 - accuracy: 0.9455 - 191ms/epoch - 957us/step
Epoch 598/600
200/200 - 0s - loss: 0.1244 - accuracy: 0.9425 - 190ms/epoch - 949us/step
Epoch 599/600
200/200 - 0s - loss: 0.1243 - accuracy: 0.9450 - 191ms/epoch - 957us/step
Epoch 600/600
200/200 - 0s - loss: 0.1241 - accuracy: 0.9435 - 192ms/epoch - 959us/step
63/63 [==============================] - 0s 1ms/step - loss: 0.1159 - accuracy: 0.9530
Accuracy: 95.30
```

Source: Script Python SAFE_MEDICATION

Figure 10 – Neural network training with 1,000 epochs

```
Epoch 993/1000
200/200 - 0s - loss: 0.0834 - accuracy: 0.9675 - 226ms/epoch - 1ms/step
Epoch 994/1000
200/200 - 0s - loss: 0.0885 - accuracy: 0.9605 - 230ms/epoch - 1ms/step
Epoch 995/1000
200/200 - 0s - loss: 0.1294 - accuracy: 0.9465 - 235ms/epoch - 1ms/step
Epoch 996/1000
200/200 - 0s - loss: 0.1296 - accuracy: 0.9565 - 215ms/epoch - 1ms/step
Epoch 997/1000
200/200 - 0s - loss: 0.0986 - accuracy: 0.9555 - 237ms/epoch - 1ms/step
Epoch 998/1000
200/200 - 0s - loss: 0.0813 - accuracy: 0.9645 - 250ms/epoch - 1ms/step
Epoch 999/1000
200/200 - 0s - loss: 0.1128 - accuracy: 0.9525 - 223ms/epoch - 1ms/step
Epoch 1000/1000
200/200 - 0s - loss: 0.0852 - accuracy: 0.9610 - 217ms/epoch - 1ms/step
63/63 [==============================] - 0s 1ms/step - loss: 0.0790 - accuracy: 0.9700
Accuracy: 97.00
```

Source: Script Python SAFE_MEDICATION

Unlike the results presented in the first attempt to change the training values by increasing the number of cases and neurons in the hidden layers, expanding the training showed great effectiveness in increasing training accuracy. It was possible to achieve an accuracy value of over 90% in learning involving 10 drugs with 2,000 cases. Even with these results, a few more tests were conducted to understand the behaviour of the neural network for different configurations. In one test, the activation function of the hidden layers was changed from ReLU to tanh. Figure 11 shows the training conducted with the neural network and, at the end, the accuracy of the system after training of 91.3%.

Figure 11 – Neural network training by changing the ReLU activation function to tanh

```
Epoch 993/1000
200/200 - 0s - loss: 0.1910 - accuracy: 0.9105 - 193ms/epoch - 964us/step
Epoch 994/1000
200/200 - 0s - loss: 0.2018 - accuracy: 0.9015 - 186ms/epoch - 931us/step
Epoch 995/1000
200/200 - 0s - loss: 0.1988 - accuracy: 0.9060 - 187ms/epoch - 937us/step
Epoch 996/1000
200/200 - 0s - loss: 0.1626 - accuracy: 0.9245 - 208ms/epoch - 1ms/step
Epoch 997/1000
200/200 - 0s - loss: 0.1764 - accuracy: 0.9195 - 204ms/epoch - 1ms/step
Epoch 998/1000
200/200 - 0s - loss: 0.1636 - accuracy: 0.9180 - 196ms/epoch - 980us/step
Epoch 999/1000
200/200 - 0s - loss: 0.1715 - accuracy: 0.9180 - 188ms/epoch - 941us/step
Epoch 1000/1000
200/200 - 0s - loss: 0.1768 - accuracy: 0.9120 - 192ms/epoch - 960us/step
63/63 [==============================] - 0s 875us/step - loss: 0.1929 - accuracy: 0.9130
Accuracy: 91.30
```

Source: Script Python SAFE_MEDICATION

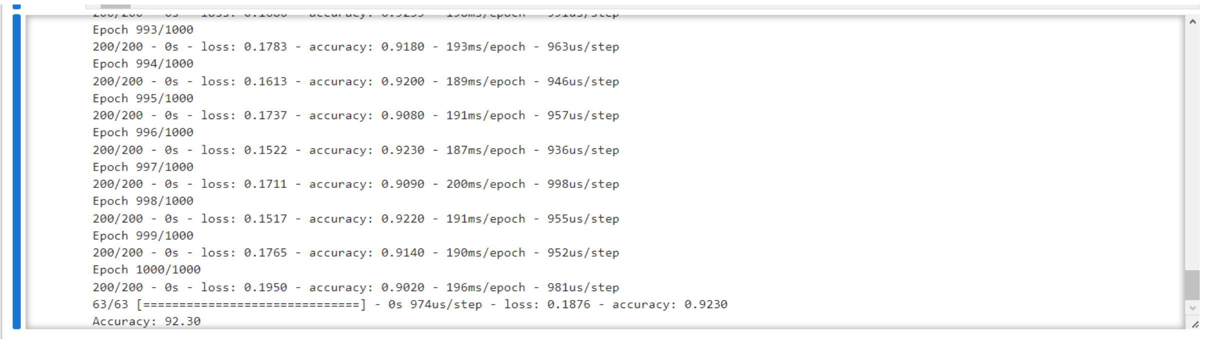
The results when using the tanh activation function in the hidden layers showed a drop in precision. Therefore, development with the ReLU function was maintained. Tests involving different learning rate values were also performed. At this stage, the learning rate was increased to 0.0001 and 0.001 in two tests. Figures 12 and 13 show the training performed with the neural networks, showing the training accuracy of the system of 92.5% and 92.3%, respectively.

Figure 12 – Neural network training with a learning rate of 0.0001

```
Epoch 993/1000
200/200 - 0s - loss: 0.1839 - accuracy: 0.9200 - 441ms/epoch - 2ms/step
Epoch 994/1000
200/200 - 0s - loss: 0.1846 - accuracy: 0.9170 - 427ms/epoch - 2ms/step
Epoch 995/1000
200/200 - 0s - loss: 0.1912 - accuracy: 0.9130 - 398ms/epoch - 2ms/step
Epoch 996/1000
200/200 - 0s - loss: 0.1838 - accuracy: 0.9210 - 409ms/epoch - 2ms/step
Epoch 997/1000
200/200 - 0s - loss: 0.2021 - accuracy: 0.9155 - 389ms/epoch - 2ms/step
Epoch 998/1000
200/200 - 0s - loss: 0.1974 - accuracy: 0.9115 - 400ms/epoch - 2ms/step
Epoch 999/1000
200/200 - 0s - loss: 0.1925 - accuracy: 0.9115 - 367ms/epoch - 2ms/step
Epoch 1000/1000
200/200 - 0s - loss: 0.1892 - accuracy: 0.9190 - 368ms/epoch - 2ms/step
63/63 [==============================] - 1s 2ms/step - loss: 0.1701 - accuracy: 0.9245
Accuracy: 92.45
```

Source: Script Python SAFE_MEDICATION

Figure 13 – Neural network training with a learning rate of 0.001

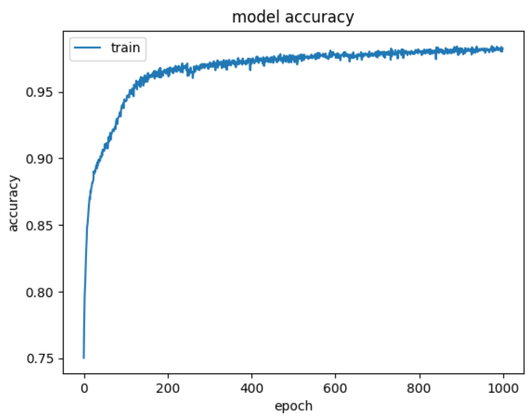


```
Epoch 993/1000
200/200 - 0s - loss: 0.1783 - accuracy: 0.9180 - 193ms/epoch - 963us/step
Epoch 994/1000
200/200 - 0s - loss: 0.1613 - accuracy: 0.9200 - 189ms/epoch - 946us/step
Epoch 995/1000
200/200 - 0s - loss: 0.1737 - accuracy: 0.9080 - 191ms/epoch - 957us/step
Epoch 996/1000
200/200 - 0s - loss: 0.1522 - accuracy: 0.9230 - 187ms/epoch - 936us/step
Epoch 997/1000
200/200 - 0s - loss: 0.1711 - accuracy: 0.9090 - 200ms/epoch - 998us/step
Epoch 998/1000
200/200 - 0s - loss: 0.1517 - accuracy: 0.9220 - 191ms/epoch - 955us/step
Epoch 999/1000
200/200 - 0s - loss: 0.1765 - accuracy: 0.9140 - 190ms/epoch - 952us/step
Epoch 1000/1000
200/200 - 0s - loss: 0.1950 - accuracy: 0.9020 - 196ms/epoch - 981us/step
63/63 [==============================] - 0s 974us/step - loss: 0.1876 - accuracy: 0.9230
Accuracy: 92.30
```

Source: Script Python SAFE_MEDICATION

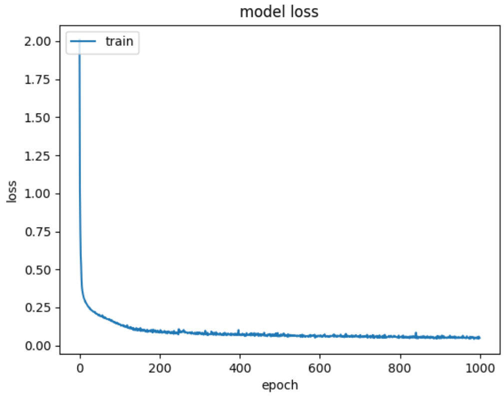
The results derived from the tests conducted with the modified learning rate were not sufficiently suitable to justify changing the value used previously. The last test performed with the neural network was definitive for the development of the system. The number of cases was increased to 20,000, and the best values from the previous tests of the neural network were retained: four layers, the two hidden layers having 128 and 256 neurons, ReLU and sigmoid activation functions, 0.0005 learning rate, 1,000 epochs and a batch size of 10. The neural network with this configuration achieved an accuracy of 98.5%. Figures 14 and 15 show the accuracy and loss graphs in relation to the epochs.

Figure 12 – Accuracy graph in relation to Epochs



Source: Script Python SAFE_MEDICATION

Figure 15 – Graph of the loss in relation to the epochs

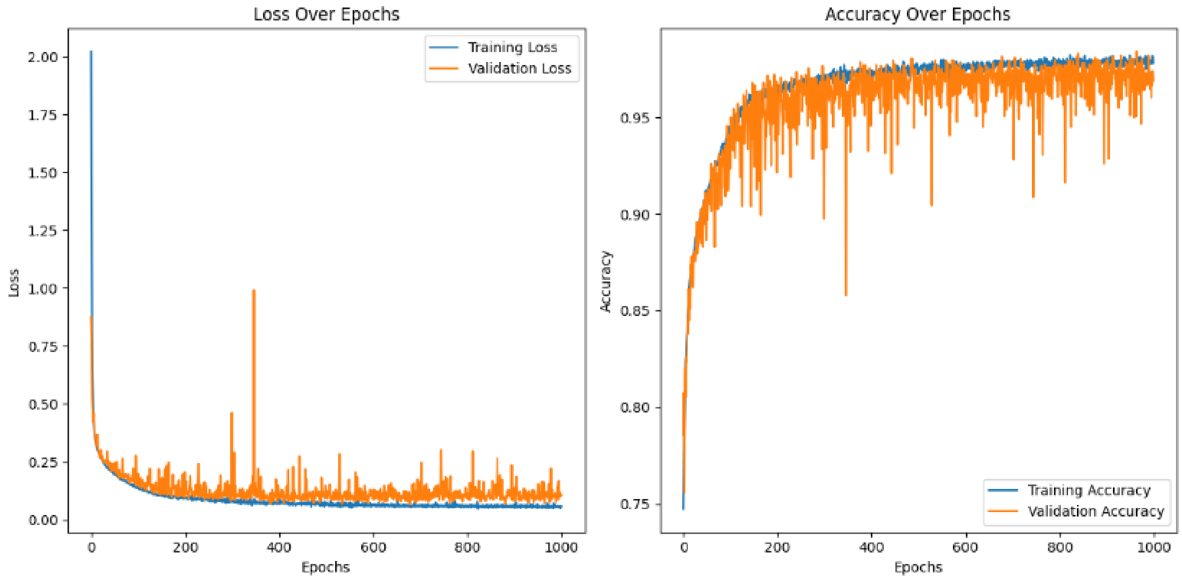


Source: Script Python SAFE_MEDICATION

4.4 Tests with unseen cases

When training a neural network, it is necessary to conduct tests to identify the accuracy of the system for new cases. This way, its prediction performance can be determined. Therefore, we chose to test the system and visualise the results using a confusion matrix, which is used to assess the quality of the output from a set of data (Confusion matrix). In addition, cases were divided to be used to validate the system during training using two values: 80/20, that is 80% of the data for training and 20% for validation and testing, and 70/30, that is 70% of the data for training and 30% for validation and testing. These proportions were used based on recommendations in the literature (GHOLAMY; KREINOVICH; KOSHELEVA, 2018). Figure 16 shows the graph of the results of the first test with the 80/20 split.

Figure 16 – Graph of accuracy and loss during training with 80/20



Source: Script Python SAFE_MEDICATION

Table 3 shows the confusion matrix.

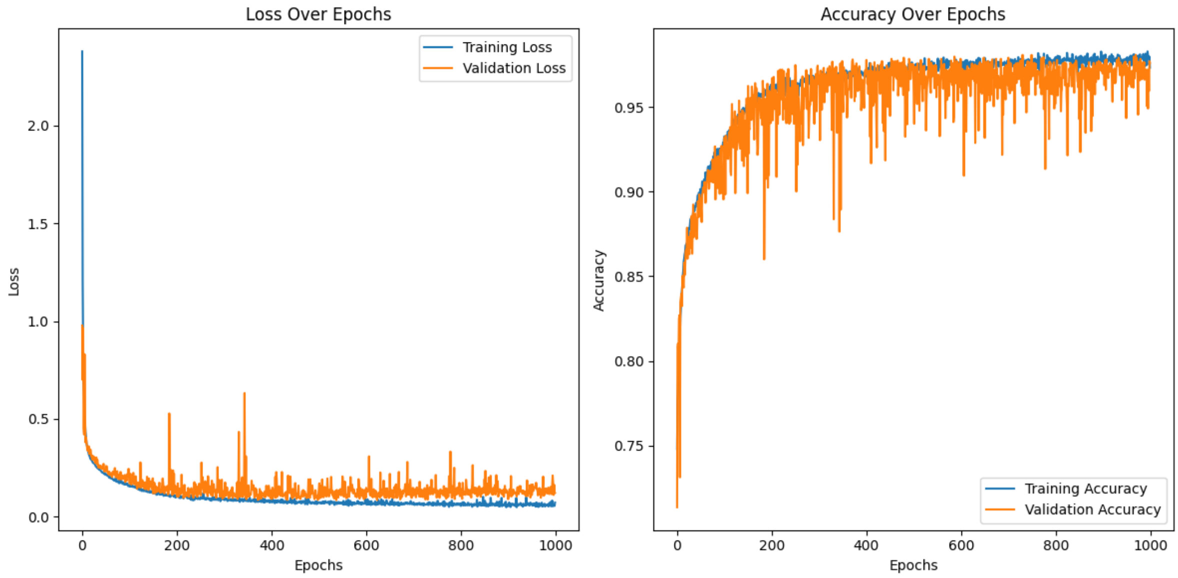
Table 3 – Confusion matrix for the 80/20 split

	Positive forecast	Negative forecast
Positive Real	318	35
Negative Real	36	1,611

Source: Elaborated by the author.

From the confusion matrix, the system's accuracy for new cases is 96.45%. The graph of accuracy and loss throughout training on the validation set with the 70/30 split is shown in Figure 17.

Figure 17 – Graph of accuracy and loss during training with 70/30



Source: Script Python SAFE_MEDICATION

Table 4 shows the confusion matrix for the 70/30 split.

Table 4 – Confusion matrix for the 70/30 split

	Positive forecast	Negative forecast
Positive Real	512	59
Negative Real	37	2,392

Source: Elaborated by the author

From the confusion matrix, the system's accuracy for new cases is 96.8%. The two tests conducted with different proportions for training and validation showed high-accuracy results for new cases, demonstrating the efficiency of the trained neural network.

5 DISCUSSION

This study describes the development of a computer program using AI capable of identifying possible cases of medication dosage errors in clinical environments. The results revealed that the application of the developed neural network can achieve an accuracy of approximately 96% by training with correct and incorrect cases. In addition, a user-friendly interface was developed for entering the drug, weight, age and dosage data; a green light is displayed if the dosage is correct and a red light if it is incorrect. A detailed discussion of these results is presented below.

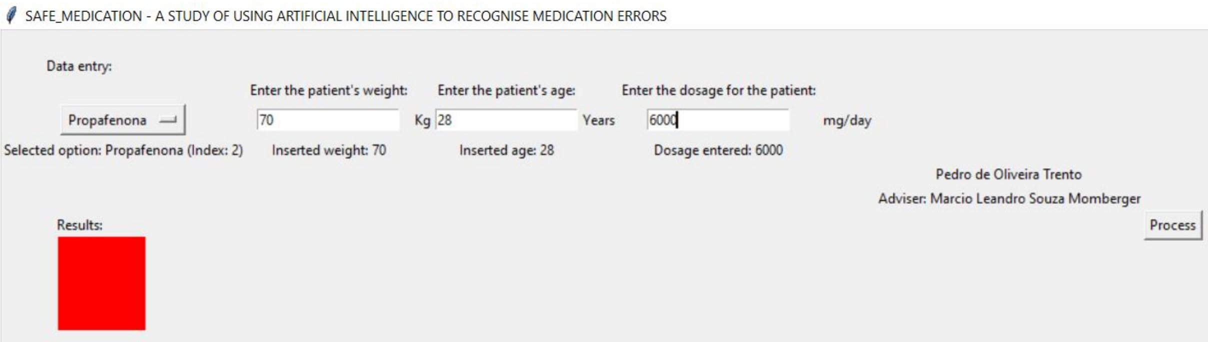
5.1 Neural network

SAFE_MEDICATION uses a neural network for the analysis of a new case of drug dosage. The result, as a response to the drug input, is generated based on previously trained information. The results of SAFE_MEDICATION evaluation contribute to the evidence of the feasibility of using AI and neural networks combined with information technology to process information to identify possible cases of medication dosage errors, offering an option for reducing the "epidemic of medical error cases" (ELLIOTT et al., 2021; LARIOS DELGADO et al., 2019).

5.2 Interface

The SAFE_MEDICATION interface was developed using Tkinter, a Python standard library for use with the Tcl/Tk GUI toolkit. The interface contains fields for entering medication, weight, age and dosage. The contribution of the interface is that stakeholders can obtain automatic detection in real time, accelerating the process of recognising a possible medication error (LI et al., 2015). Furthermore, this research contributes by suggesting that SAFE_MEDICATION can accelerate the decision-support process in drug prescription and administration by recognising possible dosage errors, indicating to stakeholders that the process needs to be revised (BAYPINAR et al., 2017). Figure 18 shows the SAFE_MEDICATION interface. The data entered in the interface correspond exactly to the case in Porto Alegre: Medication: Propafenone; Weight: 70 kg; Age: 28 years and Dosage: 6,000 mg/day. The results output by the neural network indicate that the dosage is incorrect and that the data should be reviewed by doctors, pharmacists and nurses.

Figure 18 – SAFE_MEDICATION interface



Source: SAFE_MEDICATION

5.3 Stakeholders (doctors, pharmacists and nurses)

The main idea behind SAFE_MEDICATION is to offer a computer program based on AI capable of identifying possible cases of medication dosage errors. The structure of the AI and neural network built using Python scripts aims to provide an easy-to-use tool for stakeholders in the healthcare system. The results of the program indicate that the use of SAFE_MEDICATION can mitigate the possibility of errors in prescribing medication to move on to the next stage of the process (HOWLETT et al., 2020). Another problem lies in the limited time nurses have available to search for medication information. To address this, the proposed AI and neural network systems can help in the medication checking process by recognising possible errors, thus optimising nurses' time resources (ALHARBI et al., 2021).

Additionally, the problem of handwriting can lead to problems and confusion among stakeholders. SAFE_MEDICATION can contribute by offering an interface that uses neural network training and recognises whether the prescribed dosage is correct, mitigating the risk of problems with misunderstanding the prescription (NAEEM; PARAGLIOLA; CORONATO, 2021). Moreover, it can deal with the large number of medicines that pharmacies have to handle daily (MOUATTAH; HACHEMI, 2021). Figure 23 details how stakeholders can use SAFE_MEDICATION.

6 CONCLUSION

The findings of the study indicate the effectiveness of training a neural network to recognise medication errors. An accuracy of approximately 96% was obtained. The neural network was trained using correct and incorrect cases of medication dosage. In addition, a graphic interface was developed for inputting and outputting data on new cases to be analysed by the system. The tests were conducted with different neural network configurations. After several rounds of training, an accuracy of 96% was obtained for the use of 10 drugs. Despite the accuracy, certain ranges showed problems in the performed tests. It was found that this error was due to the need for a greater number of training sessions, an increased processing capacity and a cloud server. The results of the first stage of the research indicate the feasibility of using a neural network to recognise medication dosage errors. It is concluded that the use of a neural network to reduce the risk of medication errors is feasible. With the proposed modelling, the medication errors that occurred in Porto Alegre could be avoided in the future.

In the second stage, future studies are suggested that could focus on adding more medication, recognising allergies, drug interactions, pre-existing illnesses and other factors relevant to medication errors.

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This study trains a simple neural network to predict if a medication dose is in error, which can cause a person to die or permanent damages to a person. The results revealed that the application of the developed neural network can achieve an accuracy of approximately 96% by training with correct and incorrect cases. However, only 10 drugs are tested in this study and the prediction error (1 - 96% = 4%) is still too large for patients.

Furthermore, two questions are as follows. 1. Any drug dose is based on age, sex, body weight of the patient. If there is a formula to compute the correct dose as shown in Table 2, why not just use the formula to compute. 2. If there is no formula to compute, how can the neural network judge that the dose in new unseen cases is correct, especially for new drugs?