

Computational Screening and Identification of Efficient Drug Candidates for Niemann-Pick Disease

Pallavi M. Shanthappa

Department of Computer Science School of Computing, Mysuru Campus Amrita Vishwa Vidyapeetham, India

Nidheesh M

Department of Computer Science School of Computing, Mysuru Campus Amrita Vishwa Vidyapeetham, India

Swathi LP

Department of Computer Science School of Computing, Mysuru Campus Amrita Vishwa Vidyapeetham, India

Preetham R

Department of Computer Science School of Computing, Mysuru Campus Amrita Vishwa Vidyapeetham, India

Abstract—Niemann-Pick disease (NPD) is a rare genetic ailment that impairs the body's capacity to metabolise lipids, leading to the accumulation of fatty substances in a number of organs, including the liver, spleen, lungs, bone marrow, and brain. There is currently no cure for NPD, and treatment is primarily focused on managing symptoms and providing supportive care. This study aims to provide an efficient drug candidate for NPD. By identifying the binding pockets of the NPD, suitable inhibitors were screened in PDB databases followed by molecular docking, molecular dynamics was performed to find its binding affinity and stability, followed by binding free energy estimation. The drug QDG has a high binding affinity of -7.95 kcal/mol with the NPD protein target. The 5U74-QDG complex was more stable, with an RMSD of 0.37 nm and two hydrogen bonds formed between ALA885 and LEU1045 of the 5U74 protein and the QDG drug. Additionally, it has the lowest binding free energy of -41.63 kJ/mol. The effectiveness of pharmaceuticals is shown by employing computational tools to analyse various medications. These strategies include docking, molecular simulation, and binding free energy. Based on the findings, we conclude that medicine QDG is a far more potent inhibitor of Niemann-Pick disease than competing medications.

Index Terms—Niemann-Pick disease, Drug-inhibitor, Structure-based, Molecular Docking, Charge Calculation, Molecular Dynamic Simulation, Binding Free Energy.

I. Introduction

A set of inherited lysosomal storage illnesses known as Niemann-Pick disease (NPD). Inherited lysosomal storage disorders (LSDs) are a group of rare hereditary diseases caused by lysosomal enzyme deficiencies or malfunction. [1] These enzymes are responsible for breaking down and recycling certain molecules in the body. When they are not working properly, waste products build up in the lysosomes and cause damage to cells and organs. It impairs the body's capacity to transfer lipids (fats) such as cholesterol within cells. NPD is classified into four subtypes: type A (which effects infantile), B (less severe), C (effects adults), and E (less common). Niemann-Pick disease type C (NPC) is caused by two genes, NPC1 and NPC2, which code for proteins involved in lipid transport and are the source of the disorder [2]. NPC1 primarily affects the cerebellum in the brain. [3]. A major membrane glycoprotein called NPC1 that is largely found in

late endosomes is encoded by this gene, and around 95% of patients have mutations in it [4]. Lipids abnormally accumulate in a variety of organs and tissues, including the liver, spleen, and brain, when these proteins are not functioning properly. [4] A variety of symptoms, such as respiratory issues, liver malfunction, mobility difficulties, and developmental delays, can result from this [4]. Despite the fact that it can be compromised, the membrane protein NPC1, which is mostly found in late endosomes and lysosomes, is crucial for maintaining the cell's homeostasis of cholesterol, flict people of any age, NPC often manifests in childhood or adolescence.

[4] Individuals can have vastly different levels of disease severity and progression, with some suffering a quick deterioration in health and others a more gradual course of the illness. [5] NPC cannot yet be cured, and there are few effective treatments available. [6] However, there are a number of treatments that

could aid with symptom relief and quality of life enhancement, such as the drug miglustat, which can halt the progression of neurological symptoms [3].

The goal of this study is to identify the most effective medication based on the target protein's binding residues. Second, docking was carried out to ascertain the binding affinity and examine how the drug's constituent parts interacted with the protein. Thirdly, to investigate the stability and physical motions of atoms and molecules, a simulation utilising molecular dynamics (MD) was carried out. Binding free energy was estimated to assess the change in free energy that takes place when a ligand binds to a protein. This work is motivated from our previous work on ProAll-D server, which predicts allergens and non allergens of proteins using a deep learning approach [7], and *In silico* method to predict multi-epitope design against norovirus were the study focuses on identifying novel epitopes against norovirus by using various databases [8]. In this paper, they examined methodologies such as drug-based, genome-based, chemical structure, and molecular information, and identified computational approaches that are commonly used in drug repositioning studies [9]. The Cmap was proposed and it has proven beneficial in predicting prospective treatment candidates for future experimental validation in several brain illnesses [10]. Computational methods that calculate similarities between rare and non-rare diseases, taking into account biological factors such as genes, proteins, and symptoms, inspired this work [11].

II. Methodology

A. Identification of Target Protein and Finding Binding Pockets

The human Niemann-Pick C1 protein is involved in Niemann-Pick disease type C, a hereditary lysosomal storage disorder, has a structure that may be seen in the Protein Data Bank (PDB) and is denoted with the PDB ID 5U74 [12]. It's a lysosomal membrane protein that is involved in the metabolism of lipids. It is a member of the NPC protein family. To find the binding pockets of the protein, Aggrescan [13], computational tool that predicts the location of aggregation-prone regions or "hot spots" by a combination of algorithms and statistical models is used. This tool considers various factors that are known to contribute to protein aggregation, including hydrophobicity, charge distribution, and the presence of specific amino acid

residues that are prone to aggregation which aids in the development of more effective and stable protein-based therapeutics

B. Selecting ligands for the Target Protein

Based on the hot spots of the protein target, a similarity search was performed using the tool BLASTp [14]. The protein IDs which based on the search retrieved results with a 100% query cover and 100% identity score were obtained from RCSB

[15]. The ligands associated with the identified proteins were selected as potential ligands for the target protein.

C. Molecular Docking

To achieve molecular docking, the Lamarckian Genetic Algorithm [LGA] with 25,000,000 steps and AutoDock v4.2

[16] were employed. For all ligands, the grid parameters were adjusted to size 62, 66, and 48 with centres of 30.3, 3.757, and

-21.665 for all ligands [17]. The protein-ligand interactions were visualised through LigPlus tool, and the final docked structure was viewed using Chimera [18].

2.4 Molecular Dynamics and Binding Free Energy Calculation.

Gromacs 2021.3 was used to simulate molecular dynamics (MD) [19]. The Amber ff99SB-ILDN force field was used to construct the protein's gromacs architecture [20]. Antechamber

[21] is a programme that generates force field parameters using AMBER 22 [22], was used to compute the drug's charge, and the drug's gromacs topology was created using acpype [23]. Water molecules with extended simple point charges [24] were employed with a dodecahedron box 2.0. The steepest descent minimization procedure was used to conduct energy minimization for 50,000 steps. A 50-ns MD production run is followed by a 1-ns position-restrained dynamics simulation of the system (equilibration phase) at 300 K. Xmgrace was used to construct the RMSD plot [25]. Chimera was used to create the 3D structures, and VMD was used to display them [26].

III. Results

A. Binding Pockets of Protein Target and Selected ligands

Total 40 binding pockets of the protein targets are identified. The sequences of hot spots range from length 5 to 100. Based on the hot spots obtained from the protein target, seven ligands were screened from

RCSB and selected as drug candidates to check its binding affinity as shown in Table 1, which shows its structure, molecular name and formula with ligand id.

B. Molecular Docking Analysis

The 5U74-HC3 complex has the highest binding affinity with -9.18 kcal/mol, followed by the 5U74-QDG complex with

-7.95 kcal/mol. The 5U74-HC3 complex has no H-bonds whereas the drug QDG complex has two H-bonds with ALA885 and LEU1045 of 5U74 protein. The remaining ligand along with the binding energy and interacting residues are as given in Table 1.

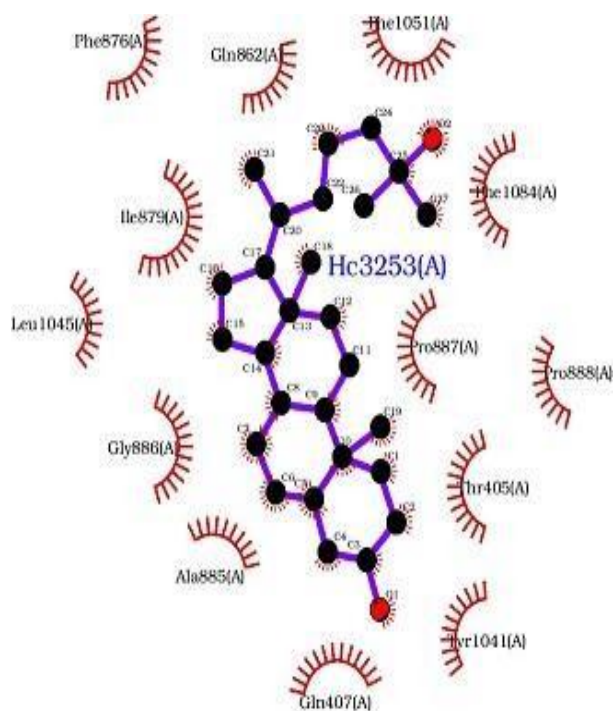


Figure. 1. (a) 5U74-HC3 complex Structure of human Niemann-Pick C1 protein with ligand HC3.

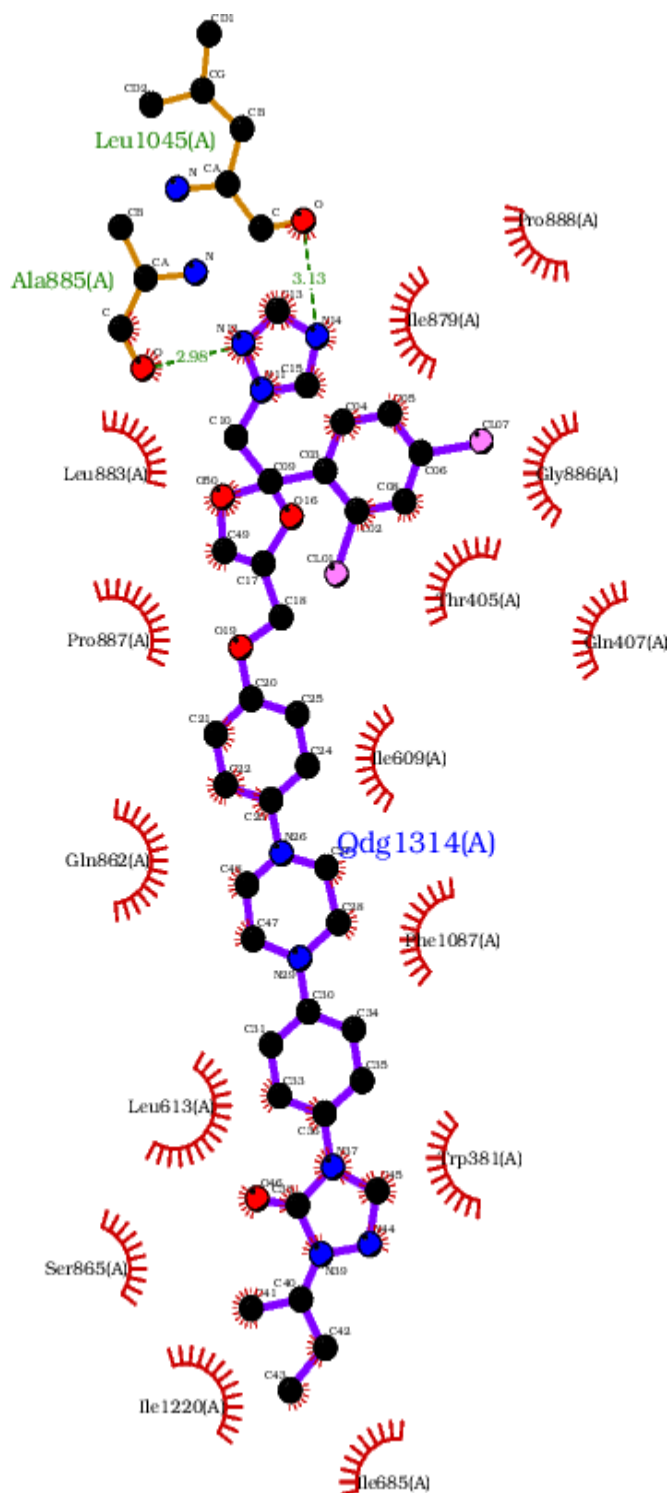


Figure. 1. (b) 5U74-QDG complex. Structure of human Niemann-Pick C1 protein with ligand QDG.

C. Molecular Dynamic Analysis and Binding energy estimation

- The Amber ff99SB-ILDN force field was used to perform a 50 ns molecular dynamics simulation of the 5U74 protein complexed with the medicines HC3 and QDG. The Gromacs topology was used for the protein, and Antechamber was used to calculate the charges and topology of the drugs. The SPC water model was employed for energy minimization. As illustrated in Figure-2(a), Root-mean-square-deviation (RMSD) calculations were utilised to estimate the stability of the 5U74-drug complexes.

- The findings show that, with an average RMSD of 0.37 nm against 0.39 nm, the 5U74-QDG complex was more stable than the 5U74-HC3 complex. The 5U74-HC3 complex exhibited the highest hydrogen bond occupancy of 11.28% between HC3 and TYR1041-5U74, followed by 7.88% between HC3 and TYR1088-5U74, and 6.52% between HC3 and GLN862-5U74. In contrast, the 5U74-QDG complex showed the highest hydrogen bond occupancy of 17.15% between QDG and SER865-5U74, followed by 8.74% between QDG and THR604-5U74, and 3.48% between QDG and TYR875-5U74.

- To evaluate changes in the 5U74 protein in combination with its medications, the root-mean-square fluctuation (RMSF) was computed, as shown in Figure 2(b). The results indicate that the QDG drug caused less fluctuation in the protein than the HC3 drug.

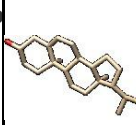
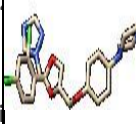
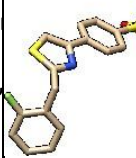
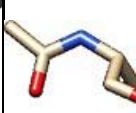

- As shown in Figure 2(c), the radius of gyration was calculated to assess the protein's compactness. The results show that protein complexes with QDG are more compact than protein complexes without QDG.


- In addition, as shown in Figure 3(a) and Figure 3(b), the binding free energies of the two complexes were determined. The 5U74-HC3 complex's binding free energy was determined to be -41.63 kJ/mol, whereas that of the 5U74-QDG complex was -42.57 kJ/mol. These results further confirm that the 5U74-QDG complex has a lower binding free energy than the other complexes.

IV. Discussion

Niemann-Pick disease gives an overview of hereditary lysosomal storage disorders (LSDs), a group of uncommon genetic diseases brought on by a deficiency or inefficiency in lysosomal enzymes. The discussion focuses on Niemann-Pick disease (NPD), which is

classified into four subtypes: type A, B, C, and E. Of these, NPC1 and NPC2 genes, which are in charge of creating proteins involved in lipid transport, are mutated in Niemann-Pick disease type C (NPC). In NPC1, the cerebellum is the brain region most impacted, and around 95% of patients have mutations in it. The present study aimed to investigate the stability and binding free energy of the 5U74 protein (Niemann-Pick disease) complexed with two drugs, HC3 and QDG. The outcomes of molecular dynamics simulations performed with the Amber ff99SB-ILDN force

Name/Formula	3D Diagram	Binding Energy
" 2-acetamido-2-deoxy-D-glucopyranose C8 H15 N O6 "		-9.18 kcal/mol
" 4-(3-bromo-((2R,4S)-2-(2,4-dichlorophenyl)-1,2,4-triazol-1-yl)-1,3-dioxolan-4-yl)methoxy)phenylpiperazine-1-yl)phenyl)-2-[(2S)-2-yl]-2,4-dihydro-3H-1,2,4-triazol-3-one C35 H37 Br Cl2 N8 O4 "		-7.95 kcal/mol
" N,N-diethyl-4-(2-fluorophenyl)methylpiperazine-1-yl)benzenesulfonamide C20 H21 F N2 O2 S2 "		-6.49 kcal/mol
" 2-acetamido-2-deoxy-D-glucopyranose C8 H15 N O6 "		-4.86 kcal/mol
" methyl (R)-(6Z)-octadeca-6,9,12-triylphosphonofluoridate H34 F O2 P "		-4.35 kcal/mol

" BIPHENYL 2, PENTAKISPHOSPHATE H15 O20 P5 "		-2.39 kcal/r

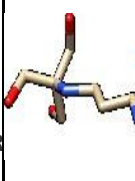
" 2-[3-(2-HYDR DIHYDROXYMETHYL- ETHYLAMINO)- PROPYLAMINO]- HYDROXYMETHYL-PR 1,3-DIOL C11 H26 N2 O6 "		-2.80 kcal/r
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Table 1: Ligands used as drug candidates for the protein target along with its structure, molecular name and formula wit

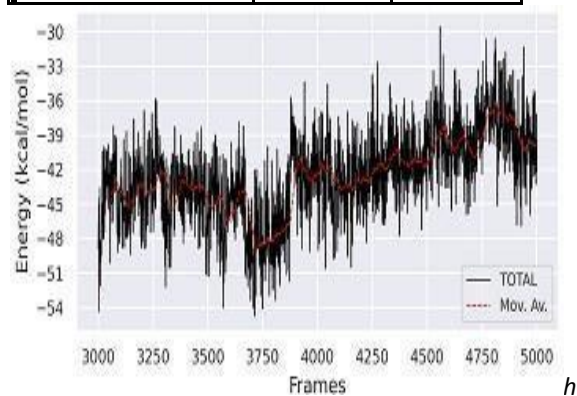


Figure. 2. (a) RMSD of the two complex .

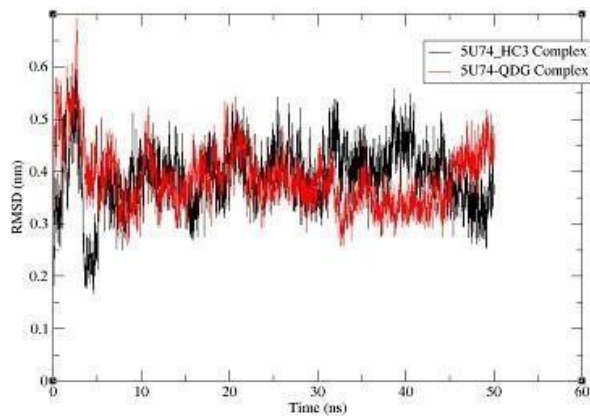
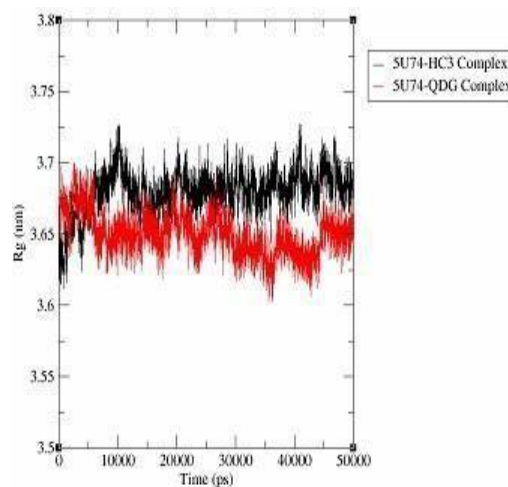


Figure. 2. (b) RMSF of the two complex .

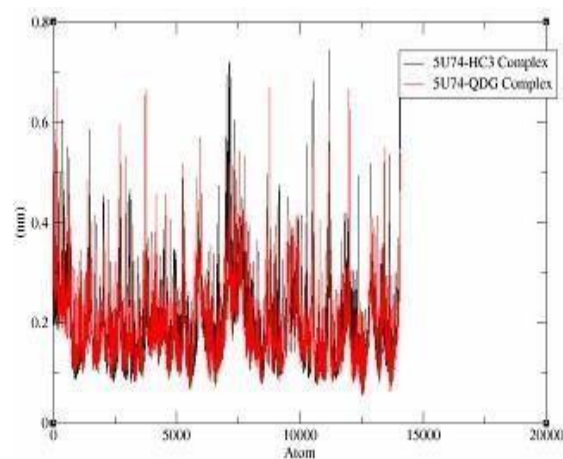
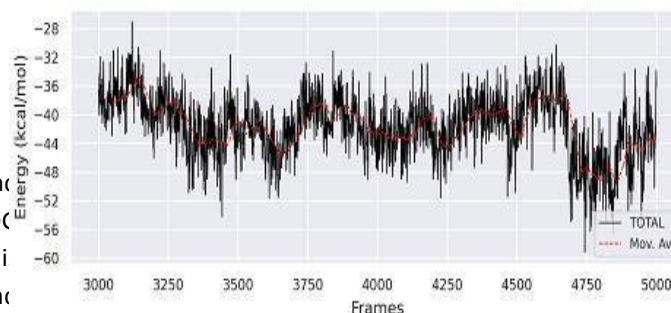


Figure. 3. (a) 5U47-HC3 Complex

Figure.3 .(b)5U74-QDG Complex



field and the Antechamber tool for drug charge and topology calculations suggest that the 5U74-QDG complex is more stable than the 5U74-HC3 complex. This conclusion is supported by the lower RMSD values and the higher hydrogen bond occupancy observed in the 5U74-QDG complex. Moreover, the radius of gyration based calculations revealed that the protein complex with QDG is more compact than in other complexes. The lower of Niemann-pick disease.

RMSF values observed for the QDG complex also indicate that QDG is more tightly bound to the protein than HC3.

References
These findings suggest that QDG could be a more effective drug candidate for the 5U74 protein. Furthermore, the binding free energy calculations showed that the 5U74-QDG complex has a lower binding free energy than the 5U74-HC3 complex. This result further confirms that the 5U74-QDG complex is more stable and has a stronger binding affinity to the 5U74 protein. In conclusion, our research sheds light on the stability and binding characteristics of the 5U74 protein when it is complexed with the medicines HC3 and QDG. The results suggest that QDG could be a promising drug candidate for the 5U74 protein and could serve as a starting point for further drug discovery studies. To support the study's computational results, additional experimental validation is needed.

V. Conclusions

In conclusion, this study aimed to identify an efficient drug candidate for Niemann-Pick disease (NPD), a rare inherited disorder that affects lipid metabolism. By performing molecular docking, molecular dynamics, and binding free energy estimation, the drug QDG was identified as having a high binding affinity and stability with the NPD protein target. The 5U74-QDG complex demonstrated strong binding with two hydrogen bonds, and QDG had the lowest binding free energy. The results of this study suggest that QDG can act as a highly effective inhibitor of NPD and may be a promising drug candidate for further investigation and development. The computational techniques used in this study can also be applied to screen other potential drugs for NPD and other diseases, providing a valuable tool for drug discovery and development. We have proposed a potential drug candidate for Niemann-pick disease which

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