ANALYSIS PAPER

INTRODUCTION

Objective:- The main objective of this project is to build a pipeline to perform a preliminary genome assembly of the source organism Listeria monocytogenes taking input as short read DNA sequence, assembling a transcriptome from RNA raw reads , annotating the genes within the genome and finally predicting the function for those genes.

Scope:-

Whole genomes can now be sequenced affordably thanks to the invention of nextgeneration sequencing. However, due to short read lengths, incomplete data, repetitive sections, polymorphisms, and sequencing errors, de novo genome assembly continues to be difficult. Scientists have been motivated to decipher the genetic information of other non-model animals because the whole-genome shotgun sequencing of some model organisms is complete. Improvements in the correctness and completeness of genomes can be somewhat facilitated by the preparation of the paired-end and mate-pair libraries as well as improving the depth of sequencing coverage. It is always necessary to put in significant additional work to achieve a full genome, such as Sanger sequencing and customized assembly methods. Whole genome sequence (WGS) analyses have been utilized to support the findings of the listeriosis outbreak investigations. As a source of organisms, Listeria monocytogenes is one of the common food-borne pathogens, Gram-positive bacteria that causes listeriosis in humans. The organism is found in moist environments, soil, water, decaying vegetation, and animals. When people eat contaminated food, they develop listeriosis.

Here we have utilized NGS data to commence with the genome assembly and chose Illumina sequence reads as it is comprehensive, rapid and the most accurate.

Input data:- The raw reads of Listeria monocytogenes DNA(SRR14252414) for genome assembly and RNA (SRR9691137) for transcriptome assembly were extracted from NCBI SRA(Sequence Read archive). For genome assembly, the scope of the sample was a mono isolate, the spot reads were 1011776, the reads read 2023552 and the bacterial sample was isolated from animal sources. For transcriptome assembly, the scope of the sample was multispecies, and the bacterial sample was tested under stimulated food processing conditions.

All the assemblies were sequentially run to finally predict the protein on Discovery high-performance computing terminal by submitting batch jobs. The scripts were modified and orderly executed by running batch scripts which displayed desired output files and accomplished all the tasks. The jobs were submitted in a scratch directory which is more performant in accessing the data. The scripts were run sequentially to run a pipeline and all the desired scripts, results, folder, and logs were made to run the scripts without an error. All the folders were shifted back to the home directory after running it from the scratch directory.

RESULTS

Tools, resources and methodology:-

1. Genome assembly

To retrieve the sequence reads from NGS of the source organism, used fasterq-dump and created a shell script getNGS.sh .After the data extraction, the reads were quality trimmed using **trimmomatic-0.39-2 version** which is a Java based quality trimmer that uses sliding window to direct the quality scores below a specific threshold and it also removes any extra adapters that get attached to beginning or end of cDNA fragments. Created a shell script trim.sh. In the script, specified trimmomatic paired end reads, threads as one which indicate server threads, phred33 indicating the quality encoding method. Thereafter, paired and unpaired output files are directed to get the same number of reads in the left and right file and low quality reads are eliminated. To remove the number of bases from the beginning used headcrop. Illuminaclip specifies the mismatch that are allowed in adapter match. The leading and trailing determine the minimum quality for trimming at the start and end of reads. Sliding window checks for the minimum average quality for bases in that window and the minimum length of reads to be kept.

After read trimming, the data were passed into the first stage of pipeline of genome assembly which is the **SPAdes genome assembler v3.13.1**. The Spades assemble the genome on the basis of overlapping reads to get the quality trimmed reads. To run the assembly created a shell script runSpades.sh and assembler will assemble the contigs, scaffolds and create an assembly graph in GFA format. After the assembly, runned a shell script runQuast.sh which checks the quality of assembly by computing various metrices N50,L50,NG50,L50,genome fraction. Finally run sbatch_assembleGenome.sh to run the whole program and assemble the genome which will create the several output ,log files and plots. The assembly is further analysed on the basis of result.txt and reports.

2. Assembling a transcriptome from RNA raw reads:-

Before taking an input RNA rawreads, builded a genome database using GSNAP which use ListeriaGmap database to perform the alignment of RNA seq reads. Built a script ListeriBuild.sh for the alignment. Used scaffolds.fasta to build the database. Following which processed input data RNA raw reads of source organism by retrieving it from NCBI SRA using fasterq-dump command. Thereafter, used **trimmomatic** tool to trim the low quality reads, clean up the reads and removing adapter remnants. This generated paired and unpaired reads. After successful trimming, the reads were assembled using **Trinity** as it reconstructs the full length transcriptome and is better than other denovo assemblers. Created a shell script trinityDeNovo1.sh to list all the left and right reads and run them in a comma separated lists. After which, shell script runtrinityDeNovo.sh was run on CPU mode 4 and the assembly commenced with working on reconstructing the transcripts using three independent software modules Inchworm, Chrysalis and Butterfly sequentially. The jellyfish extract and count the kmers from the reads, inchworm assembles initial contigs by greedily extending sequences with most abundant kmers, chrysalis clusters the overlapping contig ,build de Bruijn graph for each cluster and partitions reads between the clusters, Butterfly resolves alternatively spliced and paralogous transcripts independently for each cluster. This will result in output files in trinity denovo that will be generated in results. To analyse the trinity results created a shell script analyzetrinityDenovo.sh which stored the standard output to results as text file counting the number of trinity genes, transcripts and generate a statistics of all the transcript contigs and stats based on longest isoform per gene. Finally created a shell script sbatch_trinityDenovo.sh to combine all the shell scripts and create the desired output files and directories

3. Annotating the genes within the genome:-

To annotate genes within the genome used **blast**, **Transdecoder** and **hmmscan** to identify protein sequences similarity and protein predictions using input data .Input data containing Trinity de novo data of Listeria genome from previous module was extracted and proteins were predicted using Transdecoder which follows a 4 step process:

- 1. Transdecoder.long orf which searches the longest open reading frame and translate to amino acid sequences.
- 2. Blastp which identifies proteins similarity by aligning the long orf to guide the prediction expression process

- 3. Hmmscan which uses Hidden markov model to scan and protein domains and guide the prediction process
- 4. Transdecoder.predict which takes in ORF, BLAST Output and protein domain information to filter protein predictions to produce a protein fasta file *.pep

To begin with the protein prediction, the directories, files, results and scripts were created The bash scripts were run sequentially (longOrfs_args.sh, blastPep_args.sh,pfamScan_args.sh,predictProteins_args.sh) to extend command line arguments to make the code extensible in provided path.

The scripts were hard coded using \$preceded by the number of arguments.

- longOrf_args.sh finds the longest ORF in data taking trinity fasta as an input and producing an output in results in trinity_de_novo_transdecoder_dir
- blastPep.sh aligns the proteins which are found in longest orf to swissprot database
- pfamScan_args.sh used hmmscan tool to take query protein sequences found in the ORF's and searched them against HMM database and output the ranked list of significant matches to the sequence.
- predictProteins_args.sh The transdecoder predicts the coding regions from the ORFS according to the ORF retention criteria which is as follows:
- 1. Minimum length of ORF in a transcript sequence
- 2. A log likelihood score
- 3. Longest orf identified if ORF is fully encapsulated by coordinates of another candidate orf
- 4. PSSM (Position specific scoring matrix) computed to refine start codon prediction
- Finally run the command sbatch_transdecoder.sh script to perform BLAST and Transdecoder.
- 5. Predicting the function for those genes: The aligned predicted proteins were further used as an input data to align them to Swissprot using BLAST.

 Used KEGG (Kyoto Encyclopedia of genes and genomes) and gene ontology to retrieve the data for set of transcripts and combine the data into single annotation file. Associated SwissProt protein IDs with the transcripts to understand the function of the genes. To predict the function used **KEGG API** which is a programmatic way to access the data from a service like KEGG. In order to convert Swissprot to KEGG for protein and write the results in a tabular file, created a function getUniprotfromBlast to return the Uniprot ID from the blast line if evalue is below the threshold. If the evalue is above threshold, it returns

False. To return list of all kegg genes connected with Uniprot id created a function getKeggGene. After having uniprot id, to get kegg id we need to pass it to Kegg API. To execute KEGG api command used requests library. In order to decode the data into normal text used decode() string method and encoding type (UTF-8). To iterate over more than one line of output used result.iter_lines() and returned kegg genes. Similarly created a function getKeggOrthology() to return KeggOrthologyID using kegg genes and modeled it on getKegggenes() function. Created a function load kegg pathways to return the dictionary of pathID as keys and pathway description as values. Finally created a function addkeggPathways() to tie all the functions together to establish an output file in results as alignpredicted.txt.

INTERPRETATION:-

The genome assembly of the reference genome Listeria monoytogenes was performed using Spades assembler and for analysis used Quast. Quast compute the metrices and evaluates a genome assembly. The output file report.txt was analysed indicating the length of contigs, largest contig, GC%, N50,L75,L50.

```
contigs (>= 0 bp)
  contigs (>= 1000 bp)
                                   27
                                   21
  contigs (>= 5000 bp)
                                   19
            (>= 10000 bp)
            (>= 25000 bp)
                                   18
  contigs (>= 50000 bp)
                                   15
Total length (>= 0 bp)
Total length (>= 1000 bp)
                                   3001580
                                  2983688
Total length (>= 5000 bp)
Total length (>= 10000 bp)
Total length (>= 25000 bp)
                                  2963380
                                  2949868
                                   2932269
Total length (>= 50000 bp)
                                  2823182
 contigs
                                   32
argest contig
                                   482303
Total length
                                   2986611
GC (%)
                                   37.25
                                   228482
                                   161236
L50
 N's per 100 kbp
                                  0.00
[sardana.p@ood results_2022_12_13_19_31_42]$
```

Fig 1. **Report.txt file**

From the contig statistics, the genome is broken into 77 pieces where 27 contigs have larger or more significant contigs. The lower number of contigs usually indicates the more contiguous (better) assembly. The largest contig is 482,303 bp which means that the large pieces of genome are assembled correctly.

Here, in the output, the N50 value is 228482 bp which is the length of smallest contig after they have been ranked from longest to smallest and the sum of contig

length covers 50% of the total size of the contig. Here the L50 value is 5 which is the smallest number of contigs whose length makes up half of the genome size. Higher N50 and lower L50 values indicate better assembly quality. Similarly, higher N75 values and lower L75 values indicate better assembly quality. The N's per 100 kb is '0.00' which means there are no missing reads or base pairs in genome assembly suggesting high quality assembly without gaps.

In the GC content plot above Fig 1.

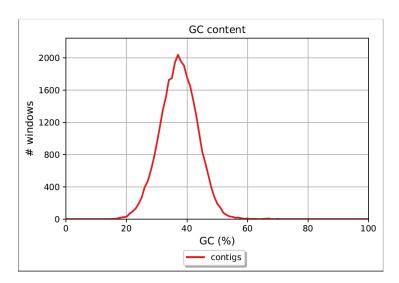


Fig2- GC content plot The GC content is around 37.9% which aligns with the overall GC content. The distribution of GC content appears to be symmetrical, bell-shaped suggesting that the GC content is uniformly distributed across the contigs.

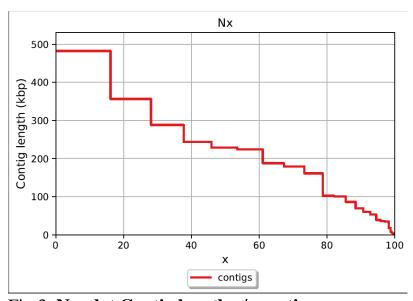


Fig 3. Nx plot Contig length v/s contigs

This plot is used to evaluate the length distribution of contigs where X-axis represents the percentage of total assembly length covered by contigs of at least certain length while the Y axis represents the length of contigs in Kilobase pairs (Kbp). At the left side (x = 0), the contigs are the longest. The plot starts around 500 kbp indicating the largest contig in the assembly around 500 kbp. The plot steps down as x increases, indicating that the contig length decreases with respect to genome. Each step represents a point where cumulative length of assembly reaches another 1% of total length.

- N50: The point where x=50. In this case, the N50 value (the contig length at which 50% of the assembly is covered) is around 228,482 bp, as indicated by a significant step near x=50.
- N75: The point where x=75. The contig length at this point is approximately 161,236 bp, indicating that 75% of the assembly is covered by contigs of this length or longer.

Towards the right side (x = 100), lengths of contigs decrease significantly where smaller contigs contribute to the final portions of the assembly coverage.

From the plot, the N50 value is high indicating that the assembly contains relatively long contiguous sequences.

The gradual decline in the plot shows moderate fragmentation, with a mix of long and short contigs.

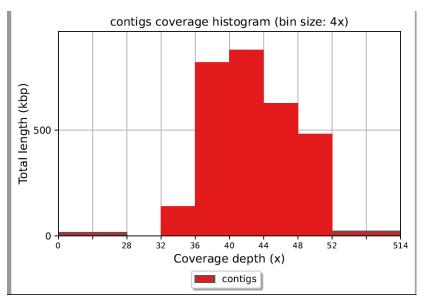


Fig 4. Contigs coverage histogram Total length v/s contigs

The coverage histogram plot (Fig.4) shows the distribution of sequencing coverage depth across the contigs in the assembly. The X-axis represents the depth of coverage which is the number of times each nucleotide is sequenced in an experiment while Y- axis represents the total length of contigs that fall within each coverage depth bin. The bin size of 4x indicates that each bar in the histogram represents the range of coverage depths grouped in multiples of 4. From the graph, the most of contigs have a coverage depth between 36x to 48x while there are smaller bars that are very low and have high coverage depths indicating fewer contigs with low coverage levels. The peak of the histogram is around 40 to 44x suggesting majority of the assembly has coverage depth in this range. This further supports the conclusion that genome assembly is moderate to good quality with consistent coverage depth across most of the contigs.

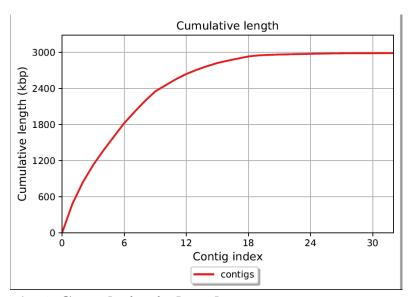


Fig 5. Cumulative index plot

The cumulative index plot (Fig.5) illustrates the cumulative length of contigs in the genome assembly as a function of the contig index where X-axis represents the index of contigs sorted by length where index 0 represents the longest contig and progresses to the shortest contig and Y-axis represents the cumulative length of contigs in kilobase pairs (kbp). The graph shows a steep increase in the beginning, indicating that the longest contig contributes significantly to the total genome assembly length. As the contig index increases, the slope of the graph becomes less steep indicating that the additional contigs are shorter and contribute less to overall length. The graph plateaus around 3000 kbp which is the total length of the assembled genome. The cumulative length does not increase significantly with the addition of the smallest contigs.

The transcriptome assembly of Listeria monocytogenes was performed using Trinity assembler and the trinity_de_novo_stats suggest that total trinity genes account for 2475 genes and percentage GC is 38.96. The total assembled bases appears to be 2243068.

Fig 6 Trinity stats.txt

The output file N10 through N50 values are computed based on assembled contigs and the longest isoform of contigs. Here the N50 values of transcript contigs and longest isoform per gene are 1548 and 1428 respectively. The assembly program produces too many transcript isoforms due to N50 values being exaggerated based on longer transcripts. this, the Nx values are computed based on single longest isoform per gene .This indicates Nx values based on single longest isoform per gene are lower than assembled contigs.

- Contig Lengths: The contig N50 values for all transcript contigs (1548 bp) and the longest isoform per gene (1428 bp) are relatively close, indicating a moderate assembly quality. Higher N50 values would indicate a better assembly.
- Average and Median Lengths: The average and median contig lengths suggest that most contigs are relatively short, which could indicate fragmentation in the assembly.
- Total Assembled Bases: The total assembled bases for all contigs and the longest isoform per gene are close, suggesting a good representation of the transcriptome in the assembly.
- GC Content: The GC content of 38.96% is within the typical range for many organisms, indicating no significant bias in GC composition.

To annotate genes within the genome used **blast**, **Transdecoder** and **hmmscan** to identify protein sequences similarity and protein predictions using input data. Reviewing the Transdecoder.predict *pep creates and output protein fasta file to filter the protein predictions taking input in ORF, BLAST and protein domain information. The fasta file predict the likely coding regions within the transcript sequences. TransDecoder identifies coding sequences based on the following criteria: 1. Minimum length open reading frame (ORF) found in transcript sequence. 2. Log likelihood score similar to what is computed by the gene 3. Coding score which is greatest when the ORF is scored in the 1st reading frame as compared to scores in other 5 reading frames. 3. The longer orf is reported when the candidate ORF is found encapsulated by coordinates of another candidate orf. The total predicted proteins were found to be 2313 from Trinity.fasta.transdecoder.pep fasta file. On the basis of reviewing the blast output alignpredicted.txt of shell script alignPredicted_args.sh, the output above

sardana.p@ood results]\$ cat al RINITY DN0 c0 g1 i1.p2 P0A442.		248	0	ø	1	248	1	248	0.0	514			
RINITY DN0 c0 g1 i1.p2 068575.			110	2	3	248	9	255	2.84e-1		295		
RINITY DNO c0 g1 i1.p1 Q6GCQ0.	1 76.590	739	172	1	6	744	12	749	0.0	1213			
RINITY DNO cO gl il.pl OSCTX6.		742	180	1	3	744	8	748	0.0	1205			
RINITY DN1001 c0 g1 i1.p1	007639.1	40.833	120	67	3	12	129	18	135	5.70e-	11	62.0	
RINITY DN1002 c0 g2 i1.p1	P94394.1	39.791	191	97		1	179	1	185	1.22e-	39	139	
RINITY DN1002 c0 g2 i1.p1	Q8DUY4.1	31.319	182	111			178		172	3.36e-	22	93.2	
RINITY DN1009 c0 g1 i1.p1	Q7AP54.1	100.000	184	ø	ø	1	184	321	504	2.21e-	128	375	
RINITY DN1009 c0 g1 i1.p1	Q7AP54.1	31.056	161	89		28	170		179	1.47e-	12	68.2	
RINITY DN1009 c0 g1 i1.p1	Q7AP54.1	100.000	184	ø	ø	1	184	321	504	2.21e-	128	375	
RINITY DN1009 c0 g1 i1.p1	Q7AP54.1	31.056	161	89		28	170	23	179	1.47e-	12	68.2	
RINITY DN100 c0 g1 i1.p1	032086.1	55.072	345	155		17	361	38	382	2.26e-	116	346	
RINITY DN100 c0 g1 i1.p1	032095.1	39.275	331	200			337	14	343	3.74e-	77	244	
RINITY DN100 c0 g1 i1.p2	032086.1	54.925	335	151	ø		335	48	382	9.13e-	112	333	
RINITY DN100 c0 g1 i1.p2	032095.1	38.585	311	190			311	34	343	1.88e-	70	226	
RINITY DN100 c0 g2 i1.p1	Q722W7.1	99.780	454		ø		454		457	0.0	928		
RINITY_DN100_c0_g2_i1.p1	PØDJP3.1	99.559	454	2	ø	1	454	4	457	0.0	927		
RINITY DN100 c0 g5 i1.p1	PØDJP3.1	99.355	155		ø		155	488	642	2.47e-	102	312	
RINITY_DN100_c0_g5_i1.p1	PØDJP3.1	99.355	155	1	ø	1	155	488	642	2.47e-	102	312	
RINITY DN1011 c0 g1 i1.p4	Q927E4.1	97.500	120		0		120		120	2.85e-	81	236	
RINITY_DN1011_c0_g1_i1.p4	Q9CIV6.1	48.696	115	59	ø		119		117	1.88e-	37	125	
RINITY DN1011 c0 g1 i1.p1	Q927E6.1	99.088	329	3	0	1	329	1	329	0.0	655		
RINITY DN1011 c0 g1 i1.p1	Q9CIV8.2	60.671	328	129	ø		329		331	9.88e-	145	414	
RINITY DN1011 c0 g1 i1.p2	Q927E5.1	96.465	198		0	1	198	1	198	3.29e-	139	389	
RINITY DN1011 c0 g1 i1.p2	Q9CIV7.1	50.794	189	89		6	194		189	4.14e-	64	199	
RINITY DN1012 c0 g1 i1.p1	P23914.2	51.892	370	175	2	1	368	1	369	1.40e-	125	386	
RINITY DN1012 c0 g1 i1.p1	P23914.2	51.892	370	175			368		369	1.40e-	125	386	
RINITY DN1012 c0 g2 i1.p1	P23914.2	31.299	508	334	6	1	502	430	928	2.29e-	82	277	
RINITY DN1012 c0 g2 i1.p1	P23914.2	31.299	508	334	6	1	502	430	928	2.29e-	82	277	
RINITY DN1012 c0 g2 i1.p2	P23914.2	31.299	508	334	6	1	502	430	928	2.29e-	82	277	
RINITY DN1012 c0 g2 i1.p2	P23914.2	31.299	508	334	6	1	502	430	928	2.29e-	82	277	
RINITY DN1014 c0 g1 i1.p1	Q8Y7M8.1	99.149	470	4	ø	5	474	1	470	0.0	951		
RINITY DN1014 c0 g1 i1.p1	Q814I2.1	59.290	479	188		2	473	3	481	0.0	574		
RINITY DN101 c0 g1 i1.p1	Q8Y7A9.1	99.603	252		ø	1	252	24	275	0.0	513		
RINITY DN101 c0 g1 i1.p1	Q92BX6.1	98.413	252	4	ø	1	252	24	275	0.0	508		
RINITY DN1020 c0 g1 i1.p2	Q9HX72.1	37.725	167	102		8	172	17	183	3.39e-	37	129	
RINITY DN1020 c0 g1 i1.p2	07VG78.1	25.161	155	114	1	5	157	314	468	5.13e-	15	75.1	

is the query id which is the target, subject id, % identity, query length, alignment length, mismatches, gap opens, evalue, and bit score. The maximum score is the highest alignment score between the query sequence and database segments which is inversely proportional to the e- value. The larger the bit score, less likely to obtain by chance than is a smaller bit score. E value is a measure of likeliness that sequence similarity is not by random chance. The percentage identity the similarity of query to the aligned sequences. The total score is the sum of alignment scores of all sequences from same database. The percent query coverage is the percent of the query length included in aligned segments.

The pipeline can effectively use such tools hhmscan, Transdecoder and BLAST if we we want to adapt the pipeline to work on another denovo genome assembly.

Finally created to predict the coding function of proteins KEGG API was used to access the data from KEGG.

CONCLUSION:-

From the above pipeline, we determined the assembly of source genome by working on distinct computational metrices like N50, L50, NA59, genome fraction, GC%,total contig length,total transcripts etc Thereafter, we annotated the genes within the genome and predicted the protein function for the genes. We can implement the new strategies in pipeline by investigating on the properties of genome we are studying such as genomic size, repeats,GC—content etc To extract high quality of DNA, various intrinsic properties can be studied effectively starting with checking the DNA quality requirements and use the best quality molecular weight. Also choosing appropriate sequencing technology will influence the cost and success of the assembly to a large extent.

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